ESSAYS ON SOLAR PHOTOVOLTAIC ADOPTION AND ELECTRICITY CONSUMPTION PATTERNS: EVIDENCE FROM PARADISE

A DISSERTATION SUBMITTED TO THE GRADUATE DIVISION OF THE UNIVERSITY OF HAWAIʻI AT MĀNOA IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

PHD

IN

ECONOMICS

AUGUST 2017

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Keywords: solar PV adoption, rooftop PV, PV penetration, electricity consumption behavior, electricity demand, renewable energy, technology diffusion

ACKNOWLEDGEMENTS

I would like to thank Hawaiian Electric Company for the amazing work collaboration opportunity, Denise Konan, Dora Nakafuji, my committee, and the Renewable Energy Planning Team for their invaluable guidance, and Talin Sokugawa and Jonathan Page for their help and suggestions. Most of all, I would like to thank my family and the Stearns family for their love and support throughout my dissertation. Any remaining errors are my own.

ABSTRACT

This dissertation studies several aspects of the widespread adoption of solar photovoltaic (PV) and how such rapid adoptions has been impacting the electric grid and consumers' electricity consumption. Chapter 1 addresses the underlying determinants of variability within net electricity load, specifically in light of increasing levels of solar saturation in Oahu. It is found that, regardless of the level of solar power generation, customer mix exerts a significant impact on the pattern and level of net load from hour to hour. The PV penetration elasticity of volatility of net electricity load shows that if the level of PV penetration in a certain area were to increase by 100%, the volatility of net electricity load on that area would be expected to increase by 3%, ceteris paribus. Taking into account the increased PV adoptions, the dynamic between residential and commercial electricity use patterns immensely reduces issues resulting from high variability in solar power generation.

To better support the integration of solar PV and other distributed energy resources, it is crucial to understand the evolution and diffusion of solar PV technology. In Chapter 2, we examine adoption trends and characteristics of residential PV adopters in Oahu, Hawai‘i. Homes having PV installations are found to be newer, larger, more energy efficient, and less costly per square foot than those without a PV installation. The analysis also reveals that early PV adopters, defined as those installing PV systems before 2012, are generally older, wealthier, more likely to own their own home, and had higher levels of educational attainment than do their contemporary counterparts.

To better understand the true impact of solar PV adoption on electricity consumption, Chapter 3 evaluates whether residential PV adopters exhibit changes in their energy demand, including responsiveness to price and weather fluctuations, following installation of PV systems. An initial examination of pre- and post-installation consumption trends within the sample dataset indicates that PV households increase their electricity usage by approximately 3% in the first year following PV adoption, with this growth rate gradually decreasing in ensuing years. Conversely, non-PV customers exhibit consistently decreasing electricity consumption over the observed time period.

To more clearly understand the impact of solar adoption on electricity consumption, we divide PV households on the basis of their PV sizing decisions. Towards this end, we first define a set of three distinct PV sizing categories: Net Import, those who “under-sized” their PV systems; Net Zero, those who sized their PV system to offset roughly 100% of their pre-solar consumption; and Net Export, those who install “larger than necessary” PV systems. Using this grouping, we find that the majority of households within the sample dataset fall under the Net Zero group, with only 2% classified as Net Export households. It is observed that Net Import households decrease consumption by approximately 4% in the first year following PV adoption. Conversely, Net Zero households consume more energy after PV installation, increasing their electricity consumption by approximately 8% in the first year following PV adoption. Net Export households exhibit the largest post-installation increase in consumption, which increases by over 30% in the first year following installation and by over 50% by the end of the fourth year post-installation.

We further estimate electricity demand showing that household responsiveness to price and weather variations is found to differ before and after installation of solar PV systems. Following PV installation, household consumption becomes more sensitive to price variation, estimated between -0.25 and -0.17. Clear differences are also observed between the various PV sizing groups in both their pre-solar responses to price, and the impact of installation on their price response. Electricity consumption in Net Import and Net Zero households becomes more elastic to price variations following PV installation. Conversely, Net Export households become less responsive to price after installation of “over-sized” PV systems.

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CHAPTER 1

Increasing Solar PV Penetration & Fluctuation in Net Electricity Consumption

1.1 Introduction

Achieving adequate supplies of clean energy for the future is a great societal challenge. Nowhere is this need more urgent than in Hawai‘i, where electricity prices are three times higher than the U.S. mainland average.[1] These high energy costs have a large impact on Hawai‘i’s economy, imposing a major burden on both local customers and businesses. As the demand for energy continues to grow, Hawai‘i has focused on transitioning to clean and affordable renewable energy sources.

Solar photovoltaic (PV) adoptions have grown exponentially within Hawai‘i. Figure B.1 illustrates annual and cumulative installations of solar PV by customer segment on the island of Oahu.[2] However, the widespread adoption of solar PV poses a number of unique challenges to electric grids which must integrate large quantities of solar generation. Solar output driven by solar irradiance is variable and intermittent, and cannot be adjusted by the utility system operator. Rapid swings in solar electricity can lead to temporary mismatches between energy supply and demand. Therefore, additional dispatchable system reserves and backup capacity may be necessary in order to maintain system reliability.

This study evaluates the impact of intermittent solar power generation under variable climate conditions on the electric grid of the island of Oahu from September 2010 to May 2014. The standard deviation of net electricity load is used as a representative variable for volatility in electricity generated by the utility.[3] An empirical analysis is performed employing a unique proprietary data set detailing electricity net load and solar penetration levels at the distribution

[1] For example, in June 2014, Hawai‘i’s electricity price was 38.7 cents per kilowatt-hour (kWh) while the U.S Mainland average was 12.9 cents per kWh.
[2] The megawatt installed capacity shown in figure B.1 is measured by the total "nameplate" capacity of solar PV of fully executed applications.
[3] Net electricity load is defined as the amount of energy met by utility generation.

transformer level.[4] It is found that higher levels of PV penetration increase variability of net load. This effect is most pronounced during daytime hours when the sun is out.

The data set employed in this study also contains detailed information on the customer mix of each distribution transformer. Using this information, we examine the combined effect of customer diversity and increased PV penetration on the shape of load profiles. It is found that, regardless of the level of solar power generation, customer mix exerts a significant impact on the pattern and level of net load from hour to hour. In residential-concentrated areas, net load exhibits two distinct peaks – morning and night. This is reflective of the underlying consumption behavior of residential customers who typically leave for school or work in the morning and return in the evening. Conversely, commercial- and industrial-concentrated areas exhibit a single midday peak corresponding to regular business hours.

The different distribution transformers considered in this study are observed to have a diversity of load patterns, depending upon their mix of customer classes. While the shape of their load profiles is primarily influenced by the customer mix and time of day, their load variability at each time period is remarkably the result of increased PV penetration level. Our result indicates that customer mix is the key driver influencing net load behavior in each area. Taking into account the increased PV adoptions, the dynamic between residential and commercial electricity use patterns immensely reduces issues resulting from high variability in solar power generation.

Over the past few years, Hawaiian Electric Company (HECO) has deployed several solar and wind monitoring devices at various locations throughout its service territory. These tools provide estimates of solar irradiance, wind speed, as well as temperature and relative humidity. In this study, we employ these measured meteorological variables along with seasonal variations to identify both the impact of climatic variations on electricity use, as well as their impact upon intermittent solar power generation. We find that wind speed negatively affects net load variability, whereas temperature exhibits a significant and positive impact. Given the semi-homogenous climate in Oahu, we further investigate the effect of temperature while taking into account humidity values in the air. Our results show that when humidity is high, increasing

[4] A distribution transformer provides the final voltage transformation in the electric power distribution system, changing voltage level between higher transmission voltages and lower distribution voltages. In the sample of this paper, there are one to three distribution transformers in a substation depending upon the size of cities or towns which the substation supplies power to.

temperatures cause net load variability to increase at a diminishing rate. This is largely due to consumers' electricity consumption behaviors. Most consumers consume more energy by turning on cooling electrical appliances when the temperature rises. This effect persists when both temperature and humidity are high. The effect of increases in both factors, however, increases the volatility in net load at a decreasing rate.

The seasonal variations are captured through time-of-day and season dummy variables. Our results indicate that the net load exhibits higher volatility during the day in winter months. During the winter, Hawai‘i's temperature and solar radiation levels are generally lower than those experienced in the summer. Changes in temperature between day and night will likely induce consumers to switch on air conditioning during the day and off during the evening. Moreover, the solar output will likely fluctuate more due to the high intermittency of solar resources in the winter, resulting in larger volatility in net electricity load.

The remainder of the paper is organized as follows. Section 1.2 reviews related literature. In Section 1.3, we introduce the details of our unique data set and describe how each variable is calculated. Section 1.4 then presents the econometric models used in this analysis. Estimation results are reported in Section 1.5. The concluding remarks and discussion are given in section 1.6.

1.2 Literature Review

Several studies address the value and impact of the intermittency of solar electricity generation upon electric grids (Hansen, 2007; Fthenakis et al., 2009; Joskoaw, 2011; Stein et al., 2012; Stewart et al., 2013). These studies claim that, in addition to certain characteristics of PV panels, various other factors affect solar electricity output, namely, the time of day, change of seasons and weather variations. As examples, Mills (2013) and Baker et al. (2013) examined the economic value of variable renewable generation and concluded that the value of new generations of PV can decrease as the level of penetration rises. Because there are additional costs associated with backup generation and solar intermittency, such costs can be minimized if utility companies know how to better operate the electric grid. If operations and investments are optimally managed in consideration of PV penetration, then additional costs can be comparatively small.

Consequently, forecasts of solar power have become necessary for the integration of fluctuating renewable energy into the grid. Various emerging studies have considered the ability to accurately forecast variability in renewable resources, such as wind and solar (Perez et al., 2010; Lorenz et al., 2011; Marquez and Coimbra, 2011; Mathiesen and Kleissl, 2011). Because solar power typically exhibits different generation characteristics as compared with power produced by conventional sources, more precise solar forecasts will enable electric system operators to better manage electricity generation in spite of fluctuating solar output.

Along with the volatility of solar output, fluctuations in electricity usage also depend upon climatic conditions. The influence of weather variations has a demand side impact on the electricity market. Weather can have diverse effects on different sectors of the economy. Moral-Carcedo and Pérez-García (2015), for example, find that changes in temperature have a large effect on the electricity demand in Spain’s service sector. On the other hand, weather variations have not been found to influence activities of the industrial sector, remaining highly and positively correlated with residential electricity demand (Amato et al., 2005; Zachariadis and Pashourtidou, 2007; Asadoorian et al., 2008; Bessec and Fouquau, 2008; Vassileva et al., 2012; Ahmed et al., 2012). In other words, the effect of climate on electricity demand depends largely on the main use of electricity, as influenced by various weather characteristics (Lam et al., 2008). Although temperature is widely known to be highly correlated with electricity consumption, it is not the only climatic variable considered in the literature. Sailor and Muñoz (1997); Yan (1998); Valor et al. (2001); Hor et al. (2005); Hekkenberg et al. (2009); Apadula et al. (2012); Tung et al. (2013) include temperature data along with other weather variables such as relative humidity, wind speed, cloud cover, and solar radiation to evaluate the impact of climate on electricity consumption. They conclude that temperature is the most significant climatic factor.

1.3 Data Description & Summary Statistics

The primary dataset used in this study was provided by HECO. The dataset was made available to the University of Hawai‘i Research Organization (UHERO) under a confidentiality agreement. Covering a period from September 2010 to May 2014, the data contains measurements of net electricity load, solar PV capacity installed, a number of customers on each rate schedule, and a variety of weather variables including average temperature, relative humidity, average wind speed and solar irradiance for 115 distribution transformers on Oahu, Hawai‘i.

For the purpose of this study, electricity net load is defined to be the amount of energy met by utility generation, while electricity gross load corresponds to the total demand, or total electricity used, by customers. Electricity gross load is met by a combination of electricity provided by the utility and electricity produced by local distributed generations such as wind and rooftop PV systems. The difference between net and gross load is, therefore, the amount of electricity produced by distributed generations. Without the precise measure of behind-the-meter solar output, gross load or the total electricity demand is rather difficult to accurately estimate. As a result, we will limit the focus of our study to the impact of increased PV penetration on net electricity load.

Table A.1 provides summary statistics of variables used in this analysis at a transformer level. The net load data analyzed in this paper consists of load measurements taken every 15 minutes, corresponding to a total of 96 daily recorded values, and covering the period from September 2010 to May 2014. Using this data, the representative daily load set for different months and years in the study period can be derived. For every month, the net load values recorded at a given time of day (e.g., 2:15 or 14:45 hours) are used to calculate the standard deviation (SD) for each of the 96 daily time periods. For example, the SD of all load values recorded at the hour of 12:30 from June 1, 2011 through June 30, 2011 are used to calculate the overall SD at the hour of 12:30 for the month of June 2011. These SD values are considered to be representative load variabilities for the given month. Table A.1 shows standard deviation of net load ranges from 3.1 kW to 1800.5 kW with the mean of 270.9 kW.[5]

The standard deviation of net load calculated for each 15-minute period captures the volatility of "net" electricity consumption. The shape of a given areas' load profile is most influenced by its customer-mix and the time-of-day, while its load volatility is largely the result of weather patterns and the level of PV penetration. We describe summary statistics and how we calculate these variables in the following sections.

1.3.1 Time-of-Day & Customer Mix

The sample data covers 115 distribution transformers servicing 199,704 distinct customers. Table A.1 shows summary statistics of the number of residential and commercial customers on

[5] Outliers and errors are eliminated by checking daily load graphs. We deleted the whole day that contains errors or outliers. Holidays are also excluded.

each transformer. Of the 199,704 total customers contained within the dataset, 21,381 are classified as commercial while the remaining 178,323 are classified as residential. The customer classification is based on their rate schedules.[6] The number of customers on a single transformer ranges between 45 and 5,459 depending on the location where the distribution transformer supplies power to. Although the number of customers significantly differs across areas and varies over time, the data on the number of customers in this study stays constant across time, due to the limited availability of historical information. We use the data on the total number of customers and customers on residential rate schedule to calculate the percentage of residential to total customers within each area, which ranges from 0% to 99% and averages 79%.

Time-of-Day

Table A.2 extends summary statistics for the standard deviation of net load by time-of-day, season and year. It is observed that the statistics of net load is higher during the day and increasing year-over-year. As expected, the average of net load volatility is greater during the day due to both the consumption behavior of customers and the nature of intermittent solar power generated by rooftop PV. An increase in average net load variations over the years suggests that increasing penetration of PV makes net load more volatile. Between each season, however, net load volatility behaves very similarly.

Customer Mix

Different transformers in our data set are observed to exhibit a variety of shapes and load profile patterns. Figures B.2, B.3, and B.4 illustrate representative daily load patterns during each year for three different customer-mixes with relatively high percentage of PV penetration. These figures depict both the annual average net load profile (black solid line) and the load volatility (green band represents the maximum and minimum values) throughout the day, and the annual kilowatt (kW) PV installed capacity (solid red line). It is observed that customer-mix exerts a significant impact on the pattern and level of net load from hour-to-hour.

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[6] Note that HECO currently does not have a separate category for industrial customers. Particularly, customers are classified into two main types: residential and commercial. Commercial customers are further subdivided into three major classes: small, medium, and large commercial dependent upon the magnitude of their electricity use. In this paper, we use the detail of customer information on each transformer to determine whether customers are industrial or commercial.

Figure B.2 is an example of a residential concentrated area. This transformer consists of 99% residential households and only a few small commercial customers. When examining the annual average net load in 2011 (solid black line), two distinct peaks are noted. The first peak corresponds to morning (5:00 am - 7:00 am) and the second peak to evening (6:00 pm - 8:00 pm). This pattern can be attributed to residents waking up in the morning and later returning following a day at work or school. Between the peaks, the net load is observed to fall during the midday when the majority of customers are outside of their homes.

Figures B.3 and B.4 show representative annual average daily net load profiles for commercial- and industrial-concentrated areas between 2011 and 2014, respectively. Commercial and industrial load profiles often display similarities depending on the type of commercial and industrial customers on the transformers. In 2011, before large gains had been made in solar PV adoption, both load profiles exhibited a midday peak corresponding to regular business hours, which gradually decreased towards a nighttime low as the majority of businesses closed for the day. Although the representative commercial transformer captured in figure B.3 is comprised only of 19% commercial customers, they are majority medium and large commercial users.[7] Conversely, the industrial-concentrated population in figure B.4 consists of 100% commercial and industrial customers.

Although the load profiles for commercial- and industrial-concentrated areas exhibit similar patterns during weekdays, they are found to diverge from one another during the weekend. Figure B.5, which displays 7-day net load profiles from August 28, 2011 to September 3, 2011, illustrates the difference in load patterns between the three primary customer-mixes transformers. It is observed that the load profile of the sample commercial-concentrated transformer is largely uniform throughout the week, with little deviation between weekdays and weekends.

Conversely, the industrial-concentrated transformer exhibits divergent load profiles between weekdays and weekends. Weekday load profiles of industrial-concentrated transformers typically mimic those of commercial-concentrated ones, exhibiting a midday peak followed by a nighttime lull. However, average weekend loads are observed to remain flat at minimum usage levels. This

[7] Note that medium and large commercial customers consume 28.9% and 41.6% of the total annual electricity consumption on Oahu. Since these commercial customers draw a large amount of electricity on this transformer, having only 19% of commercial customers is sufficient to convey a representative commercial load profile.

pattern can be attributed to the fact that industrial customers do not typically operate during weekends, although certain machines and/or electrical appliances may remain on when businesses are closed. This differs from weekend loads of commercial-concentrated areas where commercial customers such as groceries and department stores remain open throughout the weekend, leading to load profiles that exhibit little variation over the course of a typical week.

Several studies Apadula et al. (2012); Hekkenberg et al. (2009); Pardo et al. (2002); Moral-Carcedo and Vicens-Otero (2005) have shown that daily electricity demand is strongly influenced by *calendar effects*, repeated sequences of weekdays and weekends which constitute underlying periodic 7-day trends. These weekly cycles are among the main drivers of short-term variations in electricity use. The recurring trend of higher electricity consumption during weekdays is common to industrial-concentrated areas. Electricity consumption patterns of residential households, wherein midday consumption is higher on weekends when a majority of households are home, are also displayed in figure B.5.

1.3.2 Weather Variations & Solar PV Penetration

Weather data from a variety of sources is leveraged in support of this study. Weather variables are estimated by averaging 15-minute time intervals in the same manner as was used for net load data. Measurements of air temperature, relative humidity, and average wind speed were recorded by weather sensors installed in several different areas on the island of Oahu. Weather variables were queried on the basis of their relative geographic location to transformers and in the form of power per unit area. Average temperature and relative humidity data were gathered by sensors at four distinct locations on Oahu. By matching each transformer to its closest sensor, an estimate of weather variations in each area may be attained. Average wind speed data was sourced from two wind farms located on the northern coast of Oahu and is assumed to be identical for all transformers in the study.

A number of other studies employed temperature-derived variables such as cooling (CDD) and heating degree-days (HDD) when examining the impact of weather on electricity demand (Valor et al., 2001; Hor et al., 2005; Amato et al., 2005; Moral-Carcedo and Vicens-Otero, 2005; Zachariadis and Pashourtidou, 2007; Ahmed et al., 2012; Blázquez et al., 2013). Other studies elected to exploit a wide combination of weather variables including temperature, humidity, wind speed, cloud cover, rainfall, and solar radiation. (Engle et al., 1986; Filippini, 1995; Henley and Peirson, 1997; Sailor and Muñoz, 1997; Yan, 1998; Henley and Peirson, 1998; Considine, 2000; Valor et al., 2001; Pardo et al., 2002).

In this study, a number of climatic variables are utilized to better understand the effect of weather on the volatility of electricity load. Climatic variables were used in lieu of CDD/HDD as an indicator of weather variability in this paper for a number of reasons. First, HDD data are always zero in Oahu, Hawaiʻi. Although monthly CDD data are non-zero, the use of more granular data is better than the use of a daily measurement of CDD. Leading to a second justification, the frequency of our weather data is at the 15-minute time interval. The higher frequency of our variables in the data set enhances the analysis at each 15 minute.

Temperature

Hawaiʻi exhibits considerably less temperature variation compared to other states. From table A.1, the mean average temperature is 24.36 degrees Celsius with a standard deviation of 3.11 degrees. The highest and lowest average temperatures were observed in September and February, respectively.

Relative Humidity

Relative humidity is a measure of moisture in the air which plays an important role in how people perceive temperature.[8] Sweat evaporates easily when the relative humidity is low, cooling the body. Conversely, when relative humidity is high, sweat evaporates less readily leading to higher perceived temperatures. At the extreme, when relative humidity reaches 100%, sweat no longer evaporates into the air.[9] The effect of both air temperature and humidity plays a major role in a person's likelihood to utilize air conditioning. Given the relatively small variations in temperature experienced in Hawaiʻi, the additional consideration of humidity provides a better understanding of how customers perceive and respond to different air temperature values.

The summary statistics of relative humidity are shown in table A.1 with a mean of 71.19% and a standard deviation of 9.59%. The highest relative humidity during the study period was recorded

[8] Relative humidity is a percentage of the maximum amount of water vapor that the air could hold at a given temperature. 100% relative humidity implies that the air is totally saturated with water vapor and cannot hold anymore, creating the possibility of rain. However, the relative humidity near the ground is generally much less than 100%.

[9] For example, if the air temperature is 25 degree Celsius and the relative humidity is 0%, the air temperature feels like 22 degree Celsius to our bodies. But when the relative humidity is 100%, we feel like it is 28 degree Celsius.

in August where the lowest was in January. Figure B.6 depicts a negative relationship between average temperature and humidity, whereby humidity is lower when the temperature is high. This negative relationship is most pronounced when solar is greater than zero (orange dots), particularly during periods of high sunlight. This is intuitive given that sunlight reduces water vapor in the air, lowering humidity and increasing temperature.

Wind Speed

Recorded average wind speed ranges from 3 to 13 miles per hour (mph), with a mean of 7.79 mph and a standard deviation of 2.59 mph. The highest and lowest average wind speeds typically occurred during the months of July and January, respectively. Wind patterns on Hawaiʻi are strongly influenced by the trade winds. Average wind speed is estimated for 15-minute time intervals from data recorded at two different wind farms located on the northern coast of Oahu. Given the limited number of wind speed sensors, there is considerably less variation in wind speed data among transformers in the sample.

Solar Irradiance

Solar irradiance is a measure of power per unit area produced by the sun in the form of electromagnetic radiation. Solar irradiance data in this study was calculated from PV power output provided by anonymous customers with rooftop PV systems. Each customer is first mapped to a transformer on the basis of their geographic location. The average solar power produced by residential rooftop PV systems within each area is calculated in order to construct an overall solar profile. This study utilizes a normalized measure of solar irradiance with values falling between 0 and 1. Solar irradiance was found to range between 0 and 0.89, with an average of 0.19 and a standard deviation of 0.26 (see table A.1). Figure B.7 illustrates a similar pattern of average solar irradiance in winter and summer months at each time period throughout the day.

PV Penetration Level

The percentage of PV penetration reflects the percentage of daytime minimum electricity consumption on a transformer that is covered and/or generated by local rooftop PV systems. In this study, we employ percentage of PV penetration as a proxy for the amount of solar saturation on each transformer. It can be calculated as follows:

$$\text{\% of PV Penetration} = \frac{\text{PV Installed Capacity (kW)}}{\text{Daytime Minimum Load (kVA)}} \times 100 \qquad (1.1)$$

where daytime minimum load (DML) represents the minimum load for a given location during daytime (9:00 am to 5:00 pm). We calculate the value of DML of each transformer by first matching each individual distribution circuit to their corresponding transformer.[10] The DML of each circuit under a given transformer is then summed to determine the DML at the transformer level. Table A.1 shows that DML ranges between 108 and 4,412.2 kVA with a mean of 2,230.39 and a standard deviation of 896.05. The dataset detailing the amount of solar PV capacity installed on each transformer was provided by HECO. It consists only of those PV customers with executed agreements.[11] The dataset provides details on solar system size, or PV nameplate capacity, along with the date of installation.

The electricity load of each distribution transformer not only behaves differently throughout the course of the day but also changes dramatically as solar PV penetration rises. In the sample residential transformer shown in figure B.2, a clear decrease in daytime net load is observed from 2011 to 2014. This is due in large part to a significant increase in the level of PV penetration. In 2011, when the number of PV installations was relatively low, the annual net load profile showed an increasing load during the midday with a nighttime peak. By 2012, following an increase in PV installations, the midday load had dropped while simultaneously demonstrating higher volatility during daytime hours when the sun was out and solar power was readily available. Beginning in 2014, a back-feed problem on the residential-concentrated transformer is observed, with the minimum net load declining below zero. During daytime hours, the combination of lower residential power demand and higher electricity generated from rooftop PV causes the net load profile to drop substantially. The nighttime peak does not, however, exhibit the same degree of change over the study period. This implies that the nighttime behavior of residential consumers remained largely unchanged despite the rise in PV installation.

[10] Each distribution transformer in this study consists of one to four distribution circuits depending on the number of customers, their relative location, and grid infrastructure.
[11] These agreements include PV customers under Net Energy Metering, Feed-in Tariff, and Standard Interconnection Agreement.

In addition, it can be clearly observed that in figure B.2 the midday sag in residential energy demand becomes more pronounced from 2011 to 2014 as rooftop PV energy generation exceeds energy demand. During this time period, the midday variation is also observed to increase. The steep curve following the midday low rises as solar energy diminishes and late afternoon consumption rises. There is a marked disruption attributable to PV generation, which causes net load to behave differently than before. Due to this, the utility is confronted with a situation wherein it must turn down its generators when solar reaches its peak, and then later ramp them up more quickly than usual when solar power availability declines in the evening.

Figure B.4, a representative industrial-concentrated transformer, displays a dramatic decrease in daytime net load. As discussed earlier, industrial customers typically use less electricity on weekends when businesses are closed. The lower band, representing the minimum net load is observed to drop below zero starting in 2012 due to a sharp increase in the number of solar PV installations. The variation in net load increases over the course of the study period due to excess electricity generated by rooftop PV, especially during weekends when demand is at its minimum. This back-feeding during weekends lowers the average net load on the transformer over time.

1.4 Methodology

In line with the availability and description of our data in the previous section, we employ a fixed effects model, which controls for time-of-day, month and year effects, and a set of covariates. Our goal is to capture the effect of relevant variables on net load volatility. We hypothesize that the volatility of net electricity load at time *t* for each distribution transformer *i* depends on the level of PV penetration, the mix of customer classes, weather variations, time-of-day and seasonal variations.

$$Y = f(\text{PV Penetration}_{it}, \text{Customer Mix}_{i}, \text{Weather}_{it}, \text{Time-of-Day}_{t}, \text{Seasonal Trend}_{t}) \qquad (1.2)$$

The dependent variable in our analysis is the logarithm of standard deviation of electricity net load. We further employ a number of meaningful interaction effects which greatly enhance understanding of the relationships among variables in our analysis.

In the baseline model, we evaluate the impact of potential drivers of changes in net load volatility. These drivers include a percentage of PV penetration, weather variables, and time dummies.[12]

$$\ln(SDNL_{it}) = \beta_0 + \beta_1 \ln(PVPen_{it}) + \beta_2 Temp_{it} + \beta_3 Hum_{it} + \beta_4 SI_{it} + \beta_5 Wind_{it} + \beta_6 DNdum + \beta_7 SWdum + \gamma TD + \varepsilon_{it} \quad (1.3)$$

where $lnSDNL_{it}$ is the standard deviation of net load on a transformer *i* at time *t*. Note that since the variables in our model are measured at every 15 minute and vary from month to month and year to year, our time component (*t*) represents the time of day in each month and on each year. For example, the average temperature at noon on January 15th, 2013 is different from that of the same date in 2014. $lnPVPen_{it}$ denotes the percentage of PV penetration in logarithm value on a transformer *i* at time *t*. The coefficient on $lnPVPen_{it}$ (β_1) gives a PV penetration elasticity of net load volatility. In order to estimate the effect of weather variations, we include $Temp_{it}$, Hum_{it}, SI_{it}, and $Wind_{it}$ which are average temperature in degree Celsius, average percentage relative humidity, average solar irradiance, and average wind speed in mile per hour on a transformer *i* at time *t*, respectively. *DNdum* is a day/night dummy variable defined to be 1 for daytime (9:00am - 5:00pm) and 0 for nighttime (5:15pm - 8:45am). *SWdum* is a season dummy – equals 1 for summer (May to October) and 0 for winter (November to April). *TD* denotes a vector of time dummies: time, month and year dummy variables. We estimate the baseline equation (1.3) using fixed-effects estimator.

Next, to capture the impact of customer diversity and increased solar penetration on net load variation, we employ the first interaction term into our baseline equation (1.3):

$$\ln(SDNL_{it}) = \beta_0 + \beta_1 \ln(PVPen_{it}) + \beta_2 Temp_{it} + \beta_3 Hum_{it} + \beta_4 SI_{it} + \beta_5 Wind_{it} + \beta_6 DNdum + \beta_7 SWdum + \beta_8 \mathbf{RPV_{it}} + \gamma TD + \rho_{it} \quad (1.4)$$

where RPV_{it} is the interaction effect between the percentage of residential customers and log of PV penetration. Since the percentage of residential is time-invariant in this analysis, we omit its main effect in our fixed-effects model. As mentioned in the previous section, the shape of net

[12] We apply log transformation on both standard deviation of net load and percentage of PV penetration to make them normally distributed.

load profiles is greatly influenced by the mix of customers on each area, incorporating this interaction term (*RPV_{it}*) will entail the impact of increased PV penetration on the volatility of net load conditional on various values of customer mix. With the interaction term *RPV_{it}*, the coefficient on lnPVPen_{it} (β_1) in equation (1.3) changes its meaning. In equation (1.4), significant β_1 entails the main effect of PV penetration on net load volatility when the percentage of residential customers equal zero. That is, for example, a negative and significant β_1 would imply that as PV penetration increases variation of net load decreases when a transformer is fully commercial- or industrial-concentrated.

The second interaction effect is employed to assess the impact of increased PV penetration on net electricity load variation conditional on the intermittency of solar resource.

$$\begin{aligned}\ln(\text{SDNL}_{it}) \quad &= \beta_0 + \beta_1 \ln(\text{PVPen}_{it}) + \beta_2 \text{Temp}_{it} + \beta_3 \text{Hum}_{it} + \beta_4 \text{SI}_{it} + \beta_5 \text{Wind}_{it} \\ &\quad + \beta_6 \text{DNdum} + \beta_7 \text{SWdum} + \beta_9 \mathbf{SIPV_{it}} + \gamma \text{TD} + \lambda_{it}\end{aligned} \tag{1.5}$$

where *$SIPV_{it}$* denotes the interaction effect between average solar irradiance measure and log of PV penetration. The interaction effect in equation (1.5) conveys the impact of increased solar penetration on net load volatility depending on the fluctuation in solar resource. Since adding an interaction effect changes the interpretation of all the relevant coefficients, β_1 in equation (1.5) is now interpreted as the effect of PV penetration on net load volatility when solar irradiance equals zero. That is, if β_1 is insignificant, then increased in percentage of PV penetration has no impact on changes in net load at nighttime. Likewise, β_4 is now the effect of solar resource on net load volatility when percentage of PV penetration equals zero.

Lastly, we further explore the impact of weather variations on net load volatility by including an interaction effect between temperature and humidity.

$$\begin{aligned}\ln(\text{SDNL}_{it}) \quad &= \beta_0 + \beta_1 \ln(\text{PVPen}_{it}) + \beta_2 \text{Temp}_{it} + \beta_3 \text{Hum}_{it} + \beta_4 \text{SI}_{it} + \beta_5 \text{Wind}_{it} \\ &\quad + \beta_6 \text{DNdum} + \beta_7 \text{SWdum} + \beta_{10} \mathbf{TempHum_{it}} + \gamma \text{TD} + \alpha_{it}\end{aligned} \tag{1.6}$$

where *$TempHum_{it}$* is the interaction term between temperature and humidity. As mentioned in the previous section, with the relatively small variations in temperature in Hawai‘i, the level of humidity in the air can make it feel hotter or cooler. This interaction effect is used to capture the impact of both temperature and humidity on fluctuations in net load.

1.5 Empirical Results

Results of several specifications are reported in table A.3. In addition to the models specified in the previous section, we include models of two or more interaction terms to capture the effects of explanatory variables. Column (1) in table A.3 reports regression results of our baseline model (1.3) without interaction terms. The PV penetration elasticity of volatility of net electricity load is positive and statistically significant at 5%. The predicted coefficient implies that if the level of PV penetration in a certain area were to increase by 100%, the volatility of net electricity load on that transformer would be expected to increase by 3%, ceteris paribus.

The estimated coefficients for average temperature and wind speed are both found to be statistically significant at 1%. The average temperature has a positive effect on net load volatility with a 1 °C increase in average temperature increasing the volatility by 5.2%, holding other variables constant. The fluctuation in electricity demand by households when temperatures are high, resulting from increased use of air conditioning, for example, creates instability in electricity use. Conversely, lower temperatures result in a more balanced net electricity load throughout the day due to a decreased inclination to turn on fans or air conditioning.

The estimated coefficient of wind speed is equal to -0.018 and found to be statistically significant in all specifications. For every one mile per hour increase in average wind speed, the volatility of net load is predicated to decrease by 1.8%. Higher and sustained wind speed makes the weather slightly cooler reducing the need to switch on and off cooling appliances.

Both dummy variables, day/night and summer/winter dummy, are significant at 1%. The positive coefficient on the day/night dummy variable suggests that net load volatility is higher during the day than during the evening. This result is clearly shown in figure B.8 which depicts higher distributions in net load volatility during the daytime. The results in column (1) in table A.3 also indicate that the volatility of net electricity load is lower during the summer than during the winter months. Since it is generally sunnier and hotter in the summer, net electricity load is more consistent and less variable.

Column (2) in table A.3 illustrates the impact of customer mix and PV penetration on load volatility. The coefficient of the interaction term is positive and statistically significant, while the coefficient of the log of PV penetration is negative and statistically significant. This indicates that higher PV penetration increases the volatility of net load in residential-concentrated areas while reducing the volatility in commercial- and industrial-concentrated areas.

Figure B.9 displays annual net load profiles of four different transformers with comparable PV penetration levels.[13] Figure B.9a and figure B.9b depict patterns similar to those observed in figure B.2 and figure B.3, having slightly lower variation in daytime load due to lower levels of PV penetration. When comparing figure B.9c and figure B.4, it is observed that figure B.9c exhibits smaller minimum and higher average net load during the day. This difference is due primarily to the impact of excess power generation on weekends, as the transformer in figure B.9c has a smaller number of behind-the-meter rooftop PV installations.

Figure B.9d illustrates the annual net load profile of a transformer consisting of a mixture of residential and commercial customers (77% residential with several medium-sized commercial businesses). The average net load of this transformer drops marginally during the daytime, altering the shape of the load curve. As before, the daytime variability in net load is observed to have increased over time. However, this increase is less pronounced than was seen in more residential-concentrated (figure B.9a), commercial-concentrated (figure B.9b) or industrial-concentrated areas (figure B.9c). Again, it is clearly observable that customer-mix is a key factor influencing net load behavior in each area. During daytime hours, excess electricity generated by rooftop solar PV systems is in turn used by the transformer's commercial customers. The dynamic between residential and commercial demand patterns greatly reduces back-feeding and other issues resulting from high variability in net load.

Several existing studies have attempted to determine how heterogeneity in consumer characteristics and behaviors affect electricity consumption patterns using disaggregated data Espinoza et al. (2005); Verdú et al. (2006); Lam et al. (2008); Widén and Wäckelgård (2010);

[13] These 4 sample transformers have less PV penetration level than figure B.2, B.3, and B.4. Figure B.9a consists of 98% residential customers while figure B.9b comprises only 2% residential customers with two large commercial businesses. The majority of customers in the transformer in figure B.9c are commercial with two large industrial businesses and only 4% residential consumers. Figure B.9d consists of a good mix of residential and commercial with percentage of residential to total equals 77%.

Chicco (2012); Flath et al. (2012); Vassileva et al. (2012); Yang et al. (2013); Albert and Rajagopal (2013). Electric utilities are responsible for supplying power to a wide variety of different customers. It has been found that electricity consumption patterns are generally similar within a customer class while differing between classes (Chow et al. 2005). Our results, therefore, suggest that it is vital for utilities to distinguish load behavior of each customer class separately, especially when taking into account the impact of a rapid flux in distributed generations as seen with rooftop PV systems. Understanding the load patterns characterizing each customer class is of great value to a utility, not only enhancing their ability to better distribute power generation, but also targeting consumers with appropriate incentive programs.

Column (3) in table A.3 includes the interaction effect of PV penetration and the fluctuation of solar resource. The main effect of solar irradiance is negative and statistically significant, implying that when PV penetration is at 0%, as solar irradiance increases the variation in net load decreases. The coefficient estimate on log of PV penetration becomes insignificant in this specification, indicating that PV penetration has no effect on the grid at nighttime. The positive coefficient on the interaction term between log of PV penetration and solar irradiance, however, suggests that conditional on the level of PV penetration, net load becomes less fluctuating when it is sunny and there is less cloud in the sky. Given high levels of PV penetration, higher solar irradiance implies that rooftop PV systems generate higher and more consistent power output which then results in less variation in net electricity load.

Column (4) in table A.3 provides estimates of the interaction term between temperature and humidity. The negative coefficient on the interaction term suggests that when humidity is high, increasing temperatures still result in an increase in volatility of net electricity load, albeit at a diminishing rate. For example, an increase in temperature from 28 °C to 30 °C will have a smaller impact on people’s electricity consumption decisions when humidity is already high. Intuitively, this can be attributed to the fact that most consumers will have already turned on their air condition when the temperature was at 28 °C.

1.5.1 Additional Result

To capture the effect of a rapid increase in solar penetration, we further evaluate the same analysis using data only on daytime period (9:00 am to 5:00 pm). Table A.4 reports regression results from the daytime analysis. From the baseline model, the coefficient on log of PV penetration in column (1) in table A.4 is much greater in magnitude comparing to the same effect in table A.3. When we consider only daytime, a 100% increase in PV penetration leads to a 9.5% increase in net load volatility. The positive effect of temperature on net load variation, on the other hand, decreases from 5.2% to 2.2% with a 1 °C increase in average temperature. The diversity of customer types on an area also has a greater impact on net load volatility as shown in column (2).

1.6 Conclusion & Discussion

The unprecedented growth in solar PV adoptions over the past few years has resulted in remarkably high levels of PV penetration in Oahu, Hawai‘i. Given this rapid increase in PV installations, along with the intermittent nature of solar resource itself, the ability to integrate a vast amount of behind-the-meter rooftop PV systems into the grid has become a costly and perplexing proposition. This study endeavors to address the underlying determinants of variability within net electricity load, specifically in light of increasing levels of solar saturation in Oahu.

Using standard deviation of electricity net load as representative of load volatility, we find that net load becomes increasingly more volatile as the percentage of PV penetration rises. This impact, however, is not present at nighttime, implying that consumption behavior of electricity consumers may remain unaffected by the rapid growth in PV installations. We further assess the impact of customer diversity on net load volatility and find that customer mix is the key driver affecting the behavior of electricity net load on each distribution transformer. With an accelerated increase in solar penetration, the dynamic of electricity consumption behavior between different types of consumers can essentially lessen problems following higher fluctuations in electricity net load resulting from variability in solar power output.

From the utility perspective, understanding how net load changes following the rapid increase in PV installations is crucial. With a more disaggregated data set, electricity consumption patterns can be used to assess related policies and identify better pricing structures. Finally, the utility can reduce costs associated with integrating more behind-the-meter solar systems into the electric grid by fashioning appropriate incentive programs to attract the optimal mix of consumers.

CHAPTER 2

Evolution of Residential Solar Adoption in Oahu, Hawai‘i

2.1 Introduction

Innovation diffusion theory studies the stages underlying the adoption of innovations, the process of adoption decision-making, and the characteristics of adopters (Rogers 2010). Perception of a technology, generally based on the characteristics of that technology and people's level of awareness, plays an essential role in adoption decisions and, by implication, affects the speed of diffusion. The awareness stage in the innovation-decision process represents the point at which adopters gain a full understanding of a technologies' attributes, and are therefore able to progress to the decision-making stage. Innovation diffusion is facilitated through various communication networks over time, influencing the rate of adoption, the innovation decision process, attributes of new technologies, and the role of change agents. Rogers (2010) divides adopters into five categories on the basis of their behavior, attitudes, values, personality and the timing of adoption. These categories are: innovators (2.5% of adopters); early adopters (12.5% of adopters), early majority (35% of adopters); late majority (35% of adopters); and laggards (15% of adopters).

Under Roger's classification of adopters, Hawai‘i households with solar photovoltaic (PV) may be best categorized as either innovators or early adopters. However, given the rapid evolution of the Hawai‘i PV market, which presently has the highest PV penetration rate in the nation, one might surmise that Hawai‘i is progressing past the early adopter phase.[14] Hawai‘i, therefore, serves as a case study for other states presently lagging behind it in the rate of solar adoption. As the rate of solar adoption increases in other states, Hawai‘i's experiences will provide valuable insight into the unique barriers and challenges inhibiting PV uptake. It is therefore vital that we gain a better understanding of the adoption process for solar technology, and how it is evolving over time.

The primary objective of this study is to examine adoption trends and characteristics of PV adopters on Oahu, Hawai‘i. We describe both the general attributes characterizing PV adopters

[14] As of January 2016, 17% of Oahu customers have had PV installed and 32% of single-family homes on Oahu have installed solar PV.

and the evolution of solar installation trends over the years. By quantifying the various factors influencing consumers' solar PV adoption decisions, one is able to improve the efficacy of solar-related incentives and policies.

Identification of characteristics differentiating PV from non-PV households is done using detailed information on the time of installation, enabling one to observe the evolution of PV adopters over time. Homes having PV installations were found to be newer, larger, more energy efficient, and less costly per square foot than those without a PV installation. The analysis also revealed that early PV adopters, defined as those installing PV systems before 2012, were generally older, wealthier, more likely to own their own home, and had higher levels of educational attainment than did their contemporary counterparts.

To investigate the likelihood of solar adoption among residential single-family households, a logistic regression model incorporating household consumption level, solar resource availability, and demographic and housing characteristic information was developed. Empirical results derived from this model align with descriptive evidence, demonstrating that those living in larger, newer and less expensive (on a square foot basis) homes were more likely to install solar PV. Based on demographic information at a census block group level, we find that areas with a smaller household size, lower median age, higher levels of education, and higher median income were more likely to have significant solar PV adoption.

The remainder of the paper is organized as follows. Section 2.2 reviews literature related to this study. Section 2.3 introduces the proprietary dataset underlying the presented analysis and describes how each variable was processed and summary statistics were developed. Section 2.4 presents descriptive evidence for the data. Section 2.5 details the econometric methodology used in the analysis, with estimation results reported in Section 2.6. Finally, Section 2.7 offers concluding remarks and additional discussion of the results.

2.2 Literature Review

There exists a growing body of literature examining the influence of socioeconomic and customer characteristics and upon the likelihood of solar PV adoption (Keirstead 2007; Rothfield 2010; Kwan 2012; Mills and Schleich 2012; Rai and McAndrews 2012; Balcombe et al. 2013; Rai and Sigrin, 2013; Langheim et al., 2014; Chernyakhovskiy 2015; Graziano and Gillingham

2015). Utilizing zip code level data, Kwan (2012), analyzes the link between a variety of factors and the distribution of residential solar PV installation. The author found that the level of available solar resource was the most important factor influencing residential installation, with higher levels of solar insolation corresponding with increased PV penetration. Other factors exerting a positive influence on PV adoption include electricity prices, the availability of financial incentives, and median home values. The paper concluded that the likelihood of PV adoption was highest among certain groups – namely college educated individuals between 25 and 55 years old with a median income between $25,000 and $100,000 a year.

A number of other studies have employed disaggregated household-level data to identify the relationship between household characteristics and solar PV adoption. Keirstead (2007), utilizing demographic information captured in questionnaire response of 91 PV households in the UK, found that income, education, and homeownership were the primary predictors of solar adoption. A similar study by Rai and McAndrews (2012) analyzed the socio-demographics of 365 PV households in Texas using data obtained via a household survey. The survey results found that residential PV adopters had higher income levels, and were more highly educated than the average Texas resident.

Although these prior studies assessed the influence of demographics and housing characteristics on residential solar PV adoption, they failed to analyze the evolution of solar adoption trends over time. Moreover, their conclusions were based on relatively small samples, which offered no comparison between PV and non-PV households. The present study aims to fill this literature gap by analyzing the evolution of PV and non-PV household demographics in order to determine whether the prototypical solar household has changed over time.

2.3 Data Summary

2.3.1 Data sources

Consumption and PV Installation

Data used in this study were gathered from several different sources. The first dataset consists of proprietary billing information for 4,047 residential customers covering the period from January 2000 to May 2016. It was made available to the University of Hawai‘i Research Organization

(UHERO) under a confidentiality agreement with Hawaiian Electric Company (HECO), the sole electric utility on Oahu. The sample was generated by randomly selecting customers using a random sampling procedure which is explained in detail in Appendix E. Of these customers, 2,490 installed solar PV systems under the Net Energy Metering (NEM) program between February 2003 and May 2016.

Energy usage metrics and customer information, derived from two ancillary sources, were joined on the basis of customer installation numbers to form the overall dataset. The first component dataset contained monthly electricity consumption data in kilowatt-hours (kWh), account and meter numbers, and meter read dates. Billing data for non-PV customers consisted of actual monthly electricity consumption. For PV customers, electricity consumption was calculated as the difference between the amount of electricity delivered from the grid, and the excess electricity generated by rooftop solar and exported back to the grid by the customer. The second dataset contained service address, electric distribution zone, an indicator for whether a household had a solar hot water heater installed, and solar PV installation information (PV system capacity in kilowatts (kW) and date of installation).

Solar Irradiance

The second dataset, created from two ancillary sources, consists of monthly global horizontal solar irradiance data (GHI) in Watt/m^2 (W/m^2).[15] The first source, which was provided by AWS Truepower, LLC and HECO, contains detailed GHI data from over 900 gridded latitude/longitude points across the island of Oahu. The GHI data points cover the period from January 2013 through May 2016. The second source was drawn from Clean Power Research's SolarAnywhere® PV Power Map and covers the period between 2001 and 2013. It includes hourly GHI data on a 10-by-10 kilometer (km) tile. For the purposes of this study, 20 tiles encompassing different parts of Oahu were analyzed.

Housing Characteristics

The third dataset contains housing characteristics, Tax Map Key (TMK) separation, and building permit information. Housing metadata was obtained from the Real Property Assessment Division, Department of Budget and Fiscal Services, City and County of Honolulu. For each

[15] Global Horizontal Irradiance (GHI) is the solar insolation received by a fixed flat horizontal surface, representing in the unit of W/m^2.

household in the sample, the dataset provides information on total property assessed value ($), types of housing occupancy (single-family and apartment), dwelling size in square footage (sqft), year built, and number of bedrooms, bathrooms and half-baths. The TMK separation and building permit details were gathered from the Department of Planning and Permitting (DPP) and consist of census tract, census block group (CBG), and the total accepted value of solar PV installations ($) for customers with solar PV.

Census Details

The fourth and final dataset consists of census information obtained from the American Community Survey (ACS). It includes data elements reported at the CBG level including an average household size of occupied housing units, a percentage of population 25 years and over having a college degree or higher, a percentage of owner-occupied homes, median income ($) and median age.

2.3.2 Data Processing

The aforementioned datasets required considerable manipulation before they could be leveraged in our analysis. The ensuing section provides a summary of how these datasets were merged and filtered prior to analysis.

The consumption and PV installation dataset initially contained records for 5,500 residential customers. Using customer service address information as a key, data elements pertaining to housing characteristics and building permit information were joined to create a complete customer information dataset. While generating this dataset it was decided that certain customer accounts should be excluded should they meet any of the following conditions:

- customers for which the name on the property and the HECO account did not match;
- customers who had no property information on the Real Property Assessment Division website; or
- customers whose PV statuses under their HECO account and DPP did not match (e.g., customers appearing to have solar installation information on DPP but who were not classified as PV customers within the HECO database).

A total of 695 customers were excluded from the final population based on the above criteria.

Next, households residing in apartment buildings were identified using types of housing occupancy data. It was discovered that 750 households in the initial sample dataset resided in apartment buildings without solar PV. After excluding these households from the sample, there were 4,055 residential single-family households remaining in the sample dataset.

Meter read dates were used to determine the month and year for which billing data were to apply. The logic for this process is as follows: if the meter read date fell between the 1st and 15th of a given month, then the consumption data reported was assumed to be for the previous month; if the meter date fell between the 16th and the end of the month, then the consumption data was assumed to be for that month.

Solar irradiance of PV households in our sample was derived from two distinct data sources. The estimated monthly solar irradiance for households during the years 2001 to 2012 was sourced from the publically available SolarAnywhere database, while internal HECO data (AWS) was utilized for the years 2013 through 2016.

The AWS data covering the latter years in our study consists of measures taken for over 900 1x1 km grid points comprising the island of Oahu. Each household was first assigned the closest latitude/longitude grid point based on their address using Google Earth as shown in figure D.1. This mapping produces 216 distinct grid points, for which we query solar irradiance from the AWS data source. Estimated monthly solar irradiance for the period between 2013 and 2016 was then determined for each of these grid points, which were subsequently joined to the customer dataset.

Determination of solar irradiance for the years 2001 through 2012 was performed using hourly GHI data from the SolarAnywhere dataset. From this data source, we derived total monthly GHI for each of twenty different tiles which are illustrated in figure D.2. Each customer was then assigned a tile number (1-20) corresponding to their geographic location.

The SolarAnywhere and AWS datasets overlap in the year 2013. When comparing the values in each dataset for this overlapping year, we identified inconsistencies between the two measures as shown in figure D.3. It was, therefore, necessary to adjust the SolarAnywhere observations from 2001-2012 before it was combined with the AWS data in order to achieve a consistent measure of solar irradiance over the time period considered in the analysis. This was done by first pairing the AWS identifier (1-216) for each household with their corresponding SolarAnywhere tile number (1-20).

Let AWS_{it} be the estimated monthly solar irradiance of grid point *i* for month *t*, while SA_{it} is the estimated monthly solar irradiance of tile *i* for month *t*. Then let $AWS\text{-}SA_{it}$ be the estimated monthly solar irradiance on a combination of the two dataset on a location *i* at month *t*. From this process, we derive distinct 259 grid-tile combinations for customers belonging to our sample population.

For each of these aforementioned 259 combinations, GHI data is used to calculate an adjustment factor for each month in the overlapping year (2013) as follows:

$$\mathrm{AWS}_{it} = \mathrm{SA}_{it} * \lambda_{it} \tag{2.1}$$

where λ_{it} is an adjustment factor of a combination *i* at month *t*. An overall adjustment factor, $\lambda_{i,}$ is then calculated as the average of these 12 monthly adjustment factors. This overall adjustment factor is then used to scale SolarAnywhere GHI data for the years 2001-2012 to arrive at a consistent measure of solar irradiance across the study period as follows:

$$\text{Adjusted-SI}_{it} = SA_{it} * \lambda_{i} \tag{2.2}$$

where $Adjusted\text{-}SI_{it}$ is the adjusted values of SA_{it} for tile *i* during month *t*. Applying this process, we obtain monthly solar irradiance (W/m^2) for each PV household.

For each PV household, we also determine whether additional PV systems had been added to their accounts during the observed study period. The initial dataset only indicated the total (i.e., current) size of PV systems and the date on which the most recent PV system was installed. Information detailing the number of additional systems, along with their size and date of installation, was added using HECO's internal data portal. From this process, we identified 397 PV accounts with at least one additional PV system installed after the initial PV installation.

Lastly, in order to mitigate the presence of measurement error in monthly reported consumption, an additional eight accounts were excluded from the study sample. Reasons for exclusion included unexplained spikes in consumption profiles, prolonged periods of inactivity, and negative or near-zero gross consumption. The complete set of criteria governing exclusion of specific accounts is as follows:

- customer accounts whose gross consumption was negative during any of study months;
- customer accounts whose information did not report a solar PV installation, although their net consumption profiles indicated the presence of a system, having negative measures for certain months; or
- customer accounts exhibiting unusual patterns and/or inconsistent data points. The mean and standard deviation of monthly consumption were calculated for each customer. Accounts containing data points exceeding three standard deviations from the mean ($>3\sigma$ from the mean) were deleted.

Following this exclusion process, 4,047 residential single-family customer accounts were ultimately selected for use in the study.

2.3.3 Summary Statistics

The final study sample consisted of 4,047 residential single-family households, 2,490 of which had installed rooftop PV. The first PV system in our sample was installed in February 2003, while the latest was installed in May 2016. PV capacity of these systems ranges from 0.28 kW to 35.90 kW.

Table C.1 provides details of variable summary statistics along with t-tests assessing whether each variable statistically and significantly differed between the two customer groups. Household consumption was calculated using monthly usage from 2000 to 2005, excluding observations after PV installation. This measure represents the “baseline” consumption of households in the sample without the modifying effect of solar installation. It is observed in Table C.1 that PV households consume approximately 7.5% more energy than non-PV households on average. The t-test results indicate a statistically significant difference in mean electricity consumption between PV and non-PV households. The mean monthly solar resource available to households is found to be equivalent for the two groups.

Housing characteristic information was obtained at the household level. Statistically significant differences in the mean values were observed between PV and non-PV households, results of which are reported in Table C.1. Home value per square foot was found to be higher for non-PV households. However, on average, PV homes were found to be larger, newer and use less electricity on a per square foot basis.

Demographic variables captured at the CBG level exhibited slight differences in their means between the two customer groups. However, these differences were not found to be statistically significant, except in the case of median household income at a 4.3% significance level. This result implies that PV households tend to be located in areas with higher median income.

2.4 Descriptive Evidence

2.4.1 Solar Adoption Trend

This section describes the trend of solar adoption by examining how solar technology has diffused over time based on the year of PV installation. Figure D.4 illustrates the number of PV installations and cumulative PV capacity installed of households in the sample. It is observed that 16% of PV households in our sample have installed additional PV systems after the initial PV installation.[16] The size of these additional PV systems ranges from 0.31 to 15.4 kW, while the size of original PV systems varies from 0.28 to 35.9 kW.

Several factors have driven the rapid growth of solar PV in Hawai‘i. First, the availability of Hawai‘i solar tax credits and solar incentive programs have played a major role in encouraging widespread PV adoption. Coffman et al. (2016) address the effect of solar subsidies on residential PV installations, concluding that investment in solar PV is an exceptional idea for Hawai‘i’s homeowners. They argue that various incentives have made solar PV affordable to many customers, resulting in a significant increase in solar PV adoption.

Secondly, total solar PV installation costs have fallen dramatically over time. We show the trend in average installation cost of PV in our sample and the trend in the U.S. PV module price in figure D.5.[17] Average installation cost of PV for each year is calculated using the total values of solar installation obtained from DPP. Comparing the prices of PV systems installed before 2008 with those installed after 2013, we see that the total cost of PV installation has dropped by

[16] The number of additional PV systems ranges from 1 to 4 systems per customer.
[17] Source: Average value of PV modules, U.S. Energy Information Administration.

approximately one-half, increasing the affordability of solar PV and its competitiveness with other energy sources.

Declining installation costs and solar-friendly policies implemented in Hawai‘i have led to remarkable growth in both the number of rooftop PV installations and their average system size as shown in figure D.6. A PV system installed after 2013 would cost approximately 50% less than an equivalent system installed prior to 2008. This drop in installation costs has incentivized consumers to install larger PV systems. The increase in system sizes has raised an anecdotal issue of whether there exists an “over-sizing” trend in PV installation amongst residential customers (i.e., the system size chosen by some consumers may be larger than required to satisfy their energy demand). Given established PV penetration limits on each electrical circuit in Oahu, this “over-sizing” of PV systems serves to accelerate the speed at which PV penetration thresholds are met, thereby reducing opportunities for solar adoption by other households.

We next calculate each PV customer’s percentage of consumption offset by their PV systems. Figure D.7, which shows the percentage of energy offset, illustrates that most households that adopted PV before 2012 sized their PV systems to displace less than 100% of the total energy that they consumed. In contrast, the majority of households adopting PV after 2012 installed systems that offset, on average, 100% of household consumption demand. Figure D.7, therefore, shows that “over-sizing” of residential PV systems is not widespread. Rather, the increase in average PV system size observed can be thought of as a natural progression from the “under-sized” systems installed by early adopters. This result is not entirely surprising given the higher PV installation costs in the past, larger-than-necessary PV systems were likely not financially optimal for most residential households.

2.4.2 Characteristics of Adopters & Non-Adopters

Despite the unprecedented growth in residential solar adoption in Hawai‘i over the past decade, little attention has been given to examining the types of consumers likely to place solar PV on their homes. As more households adopt solar PV, the demographics and housing attributes of adopters also change. In this section, we examine differences in both demographics and housing characteristics of residential PV adopters and non-PV households on Oahu, Hawai‘i. Using detailed information on the time of solar installation, we are not only able to identify which factors are most predictive for solar adoption, but whether these factors are changing as the technology evolves over time.

Housing Characteristics

Age of Homes

Since the ideal location for solar PV is on a home's rooftop, it is critical to consider the roof's age and condition before installing a PV system. More recently built homes are generally less likely to require roof replacements to accommodate rooftop solar PV. As a result, one would expect consumers residing in newer homes to be more likely to install rooftop PV systems relative to those in aging homes. Figure D.8a illustrates that, in Hawai‘i, the majority of PV adopters live in newer homes. However, we also find that the homes of early adopters (installation prior to 2007) are typically older than those of both recent PV adopters and non-PV customers.

Home Values

Home value per square foot is calculated using total assessed property value and home size. From figure D.8b, we find that on average PV homes cost less per square foot than non-PV homes.

Home Size

Larger homes generally have more rooftop space, resulting in an increased likelihood of PV adoption. This is illustrated in figure D.8c, which shows that the homes of PV adopters are larger than non-adopters' homes on average.

Consumption Level

In terms of consumption level, we calculate an average “baseline” electricity consumption of each household in the sample. As can be seen in Figure D.8d, most households that adopted PV before 2010 consume less electricity on average than both recent PV adopters and non-PV adopters. However, the trend of solar adoption has been transitioning towards high consumption households in recent years.

Home Energy Intensity

Given that increased dwelling size is highly correlated with higher levels of electricity consumption, we calculate an energy intensity index based on household electricity use per square foot.[18] We observe in figure D.8e that the homes of most PV adopters are more energy efficient than those without PV. This supports finding from previous studies that adoption of solar PV is correlated with investment in energy efficiency measures (Haas et al. 1999; Dato 2015). In other words, PV households are more energy-conscious and likely to conserve electricity.

Demographics

Age

Although data limitations restrict our ability to determine the exact age of individual PV households in the present study, census level data nonetheless provides some insight. In figure D.9a we see that most households installing PV before 2009 were typically located in areas having higher median age than non-PV households and recent PV adopters in the sample. A decreasing trend in the median age of PV adopters can be observed in the figure, implying that PV adoption has been transitioning towards younger age groups.

Income

Due to the high upfront cost of PV, households with greater disposable income and better credit capacity are more likely to purchase solar PV. In figure D.9b we find that the majority of households that adopted solar PV before 2012 lived in more affluent areas as compared to recent PV households and non-PV households. The decrease in the price of PV panels in recent years as shown in figure D.5 has led to a boom in the residential solar market. However, this growth in solar PV has not been uniformly distributed across the range of household incomes. Our analysis of the Hawaiian solar market reveals that the diffusion trend is migrating to areas having lower median income. This observation implies that there may be fewer barriers to solar adoption

[18] Average home energy use per square foot is calculated by dividing each household's average baseline pre-solar electricity consumption by home size (sqft).

among lower income households than there were in the past, resulting in increased rates of adoption in this consumer market segment.[19]

Homeownership

The percentage of owner-occupied housing units exhibits a similar trend to median income. In figure D.9c, we observe that households that installed PV before 2012 were typically located in areas with higher percentage of owner-occupied homes. Although the correlation between owner-occupancy and PV adoption rates has lessened in recent years, it may still represent a limit to the growth of PV adoption due to their requiring rooftops or outdoor/unshaded spaces.

In Oahu, roughly 42% of properties are renter-occupied and many owner-occupied properties are located in multi-unit buildings or high-rises where it is technically unfeasible to install solar.[20] This poses a particular challenge for solar diffusion growth given that renters do not have the authority to install solar panels, reducing the number of potential solar PV installation sites. Furthermore, even for properties where solar installations are technically feasible, rental property owners are not incentivized to invest in PV since they generally do not bear financial responsibility for electric bills. When tenants are responsible for paying for their own electricity, landlords have no incentive to install PV systems. In arrangements where rent is fixed and includes electricity cost, tenants have little to no incentive to conserve energy should the landlord elect to install solar. As a result, landlords would bear the risk of paying for excess energy usage on top of the cost of solar installation, discouraging them from adopting solar PV.

Education

Educational attainment is also an essential factor in determining the likelihood of PV adoption. Figure D.9d demonstrates that the majority of PV adopters before 2012 resided in more educated areas. Using educational attainment as a proxy for awareness of technology, highly educated individuals are more likely to adopt solar as they are generally more knowledgeable and

[19] In recent years, solar companies have offered a number of different financing options to prospective customers in order to help offset the initial cost of solar installation. Potential PV adopters may elect to own their own systems by buying them outright or borrowing against the value of their property through mortgage refinancing via tax deductible “green energy” loan programs. For households with less financial liquidity and/or lower credit scores, leasing options and Power Purchase Agreements are also available and require no large upfront expense. The variety of financing options along with tax credits and other financial incentives will open the solar market to those with limited access to capital, including lower income households and renters.

[20] 2011-2015 American Community Survey 5-Year Estimates

environmentally aware. Given the complexity of solar technology, it is not wholly unexpected that early adopters were more highly educated. The declining trend in educational attainment among PV households observed in figure D.9d may signify that the educational barrier to solar technology has lessened as more readily understood information about the technology becomes available through a variety of channels.

Family Size

We find that family size does not differ among PV and non-PV adopters. For each year of installation, average household size is roughly identical to those without solar PV as seen in figure D.9e.

2.5 Structural Model

The objective of this study is to explore the likelihood of households installing solar PV through an evaluation of the determinants of solar PV adoption among residential households in Oahu, Hawai‘i. Towards this end, we develop a logistic regression model for PV technology adoption wherein households make a decision in accordance with their preferences by maximizing the utility of their energy consumption subject to limitations on their budget constraints. In particular, we explore which factors drive household *i* to install a solar PV system. The model dependent variable is a binary response, taking on the value of 1 if household *i* installs PV and 0 otherwise. That is,

$$Y_i = \begin{cases} 1 & \text{if a household } i \text{ installs a PV system;} \\ 0 & \text{not install} \end{cases}$$

The study employs several variables that are hypothesized to affect the likelihood of solar adoption by residential single-family households. These relevant variables include households' pre-solar electricity consumption, available solar resources, solar hot water heater (SWH) installation, housing characteristics, and demographic information.

A household's mean pre-solar consumption is calculated by averaging their monthly electricity usage from 2000 to 2005, excluding any post-solar observations. This household average pre-solar usage represents their baseline household energy demand before PV installation. To measure available solar resources we use the maximum amount of solar resource available to a given household during the 12-month pre-solar period. The presence of a SWH is captured via an indicator variable that takes the value of 1 if a household has an installed SWH and 0 otherwise.

Household level characteristic variables include property value per square foot, age of the home and home size. Demographic characteristics, which are gathered at the Census Block Group level, include education attainment (percent of the population 25 years-old and over that have a college degree or higher), average household size of occupied housing units, percentage of owner-occupied homes, median age and median income.

2.6 Empirical Results

Table C.2 reports the marginal effects of the logit model. We find that a household's probability of installing PV increases with their electricity consumption, confirming earlier findings in the literature that higher energy consumption motivates installation of solar PV systems (Balcombe et al., 2013). In California, Borenstein (2015) found that solar adoption was most prevalent amongst the highest electricity users. This finding was due in large part to a steeply-tiered electricity pricing structure under which sample households faced higher marginal prices at higher-tiered usage levels. Although Hawai'i electricity rates are flat, high prices nonetheless serve to incentivize households to reduce their electricity costs through solar adoption.

In addition to PV system size, PV energy output is largely determined by the availability of solar resources at a household's location. With greater solar resource availability, households can expect higher energy production, leading to more substantial energy bill savings and a higher return on investment. As a result, one would anticipate that consumers residing in areas having greater available solar resources are more likely to invest in solar PV (Kwan 2012; Crago and Chernyakhovskiy, 2014). However, the results of our study reveal that the amount of solar resources available to Hawai'i households do not significantly impact their likelihood of solar adoption. This deviation from the results of prior studies is largely due to the uniformity of solar radiation levels across Oahu.

The results of this study are consistent with the findings of previous literature in consumers' housing characteristics and demographic information (Keirstead 2007; Rothfield 2010; Leenheer et al. 2011; Willis et al. 2011; Kwan 2012; Mills and Schleich 2012; Balcombe et al. 2013; Rai and McAndrews 2012; Rai and Sigrin, 2013; Davidson et al. 2014; Langheim et al., 2014;

Chernyakhovskiy 2015; Graziano and Gillingham 2015). We find that housing characteristics, reported in table C.2, statistically and significantly influence the probability of PV installation. Empirical results indicate that the likelihood of solar adoption increases amongst individuals residing in newer, larger and less expensive homes (measured on a per square foot basis). Newer homes typically have better roof conditions which more easily facilitate PV system installation, while larger homes are correlated with higher electricity consumption. Although the negative relationship between home value and the likelihood of solar installation seems counterintuitive, the result is nonetheless consistent with our descriptive finding shown in figure D.8b that most PV homes have a lower cost per square foot than non-PV homes.

When considering demographic information, we find that the probability of solar adoption increases in areas with higher median household income, smaller family size, lower median age, and greater levels of educational attainment.[21] Although previous studies have found that motivation to adopt solar increases with family size (Keirstead 2007; Balcombe et al. 201), we find a negative relationship between the probability of solar adoption and the number of individuals in a household. Although larger households tend to consume more electricity, which would lead to a higher probability of solar adoption, they are also more likely to be financially constrained by other household expenses.

Homeownership is found to have an insignificant impact on solar installation despite our initially predicting that homeownership would be highly predictive for solar adoption. This result may be due in part to the influence of other attributes, such as age and income, which are highly correlated with homeownership.

The presence of a SWH is found to have a significant effect on the likelihood of PV adoption, with households having a SWH being inclined to invest in solar PV.[22] This result is consistent with our earlier finding, discussed in the Descriptive Evidence section, that PV homes are more energy efficient.

[21] The effects of these factors may not be straightforward due to interactions of a range of causal factors.
[22] Note that in June 2008, Hawaii enacted legislation requiring SWH to be installed on all single-family new home construction, with a few exceptions (S. 644, 2008). Due to this building energy code, the presence of SWH installation may not be a significant indicator for the likelihood of solar adoption in the future. In the study sample, we find that only 0.6% of PV homes with SWH were built after 2008.

2.7 Conclusion and Discussion

As national energy policy initiatives continue the push towards clean energy, exemplified in Hawai‘i’s embracing of 100% Renewable Portfolio Standards (RPS), there exists an increased urgency to judiciously divest from traditional fossil fuel based technologies and re-tool using renewable resources for distributed generations (DG) and other modern technologies. Foundational planning models need to be enhanced through the integration of refined behavioral knowledge in conjunction with physical grid constraints, so as to better support sustainable and efficient diffusion of distributed PV.

To better support the integration of solar PV and other distributed energy resources, it is crucial to understand the evolution and diffusion of solar PV technology. By evaluating the trends underlying solar adoption on Oahu, this study revealed that the likelihood of solar adoption was greatest in newer, larger, more energy efficient and less expensive (per square foot) homes. Moreover, households living in areas with higher median household income, having smaller family size, lower median age, and greater levels of educational attainment were found to be more likely to install solar PV. We also found that having a SWH was the single strongest predictor of solar PV adoption among residential single-family households.

Future research opportunities abound, including examining the growing trend in solar PV adoption among non-residential customers. Beyond a per-kWh energy charge, such non-residential customers are also subject to demand charges which determine the rate schedule to which they belong.[23] Due to this fundamental difference from residential households, their motivations for PV adoptions can differ greatly from the factors reported on in this study. For non-residential customers, PV installation can serve to drastically reduce their peak demand, given their consumption is typically highest during daytime hours which corresponds with peak solar PV energy production. As a result, the installation of solar PV lessens the probability of their switching to higher pricing schedules, further reducing their cost of electricity.

Another topic worthy of further study is the potential of battery storage uptake. The rapid decline in the cost of battery storage technology combined with changes to existing solar incentive programs, which limit the amount of energy consumers can export to the grid, significantly

[23] Demand charges are typically based on the highest level of electricity demand measured in kW.

increase the potential influence of battery storage in the near future. Additionally, since the impact of battery storage discharge behavior on the electrical grid will likely differ significantly from that of solar technologies, it is vital to assess how the grid may best leverage increased distributed solar and battery storage penetration to help meet Hawai‘i’s 100% RPS goal.

CHAPTER 3

Impact of Solar Adoption on Residential Electricity Demand

3.1 Introduction

Hawai‘i has long struggled to identify practical and effective solutions to the unique challenges facing its energy industry. These challenges arise in large part due to the state's heavy reliance on imported fossil fuels for energy generation and the isolated, self-contained, nature of its electric grid. As a result, Hawai‘i electricity prices are significantly higher than the U.S. national average and, as shown in figure G.1, highly correlated with the price of crude oil.[24]

Given the high electricity prices in Hawai‘i, the relative economic benefit derived from solar photovoltaic (PV) technology is greatly enhanced, leading to a high rate of solar PV adoption.[25] This study estimates electricity demand on Oahu, Hawai‘i, examining not only how electricity usage is impacted by price variations, but how the installation of solar PV and resulting solar PV sizing decisions affect household electricity consumption patterns.

Figure G.2 illustrates the relationship between residential monthly electricity consumption in kilowatt-hours (kWh) and electricity price for Hawaiian PV and non-PV customers in the study sample from January 2000 to May 2016. It is observed that following the 2008 oil price shock, which resulted in a spike in Hawai‘i electricity rates, average energy demand has been steadily declining. Clear seasonal patterns in average monthly consumption are observable within both the PV and non-PV customer groups, although the trend begins to exhibit fluctuations towards the end of the study period as solar PV penetration rises. Variations in consumption among PV households between summer and winter months become more pronounced beginning in 2013 when the proportion of PV customers in the study sample exceeded 70%.

One of the most important questions relating to post-solar consumption behavior is whether PV households consume more electricity following adoption. The intuition that solar PV adoption results in increased electricity consumption stems from the perception that the marginal cost of

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[24] Over a 15-year period beginning in January 2000, the price of electricity in Hawai‘i ranged from a low of 15 cents/kWh in 2003 to a high of 40 cents/kWh in 2008.

[25] Cumulative PV installations have risen from under 1 megawatt (MW) installed capacity in 2005 to over 280 MW in mid-2015, with over 95% being customer-sited installations.

electricity produced from solar systems is zero, thereby resulting in increased energy demand amongst PV adopters. However, households that install rooftop PV systems are typically faced with high upfront installation costs. The energy payback period and the manner in which the installation is financed will dictate the true price of solar energy production for a given household.

This study evaluates whether PV adopters exhibit changes in their energy demand, including responsiveness to price and weather fluctuations, following installation of PV systems. An initial examination of pre- and post-installation consumption trends within the sample dataset indicated that PV households increase their electricity usage by approximately 3% in the first year following PV adoption, with this growth rate gradually decreasing in ensuing years. Conversely, non-PV customers exhibited consistently decreasing electricity consumption over the observed time period. However, this cursory analysis considers PV adopters as a homogenous group.

To more clearly understand the impact of solar adoption on electricity consumption, this study divides PV households on the basis of their PV sizing decisions. Towards this end, we first define a set of three distinct PV sizing categories: Net Import, those who "under-sized" their PV systems; Net Zero, those who sized their PV system to offset roughly 100% of their pre-solar consumption; and Net Export, those who install "larger than necessary" PV systems. Using this grouping, we find that the majority of households within the sample dataset fall under the Net Zero group, with only 2% classified as Net Export households.

Following the division of PV households into distinct categories on the basis of their PV sizing decisions, it is possible to assess how solar installation influences their electricity consumption behavior. It was observed that Net Import households decrease consumption by approximately 4% in the first year following PV adoption. Conversely, Net Zero households consume more energy after PV installation, increasing their electricity consumption by approximately 8% in the first year following PV adoption. Net Export households exhibit the largest post-installation increase in consumption, which increases by over 30% in the first year following installation and by over 50% by the end of the fourth year post-installation.

In order to evaluate the dynamics of electricity demand in PV and non-PV households, an empirical model was developed in this study. We first measure the "baseline" electricity demand of PV and non-PV households utilizing pre-solar observations from January 2000 to December 2009. Analysis of this data reveals that electricity consumers are price-inelastic. In the baseline period (2000-2009), the price elasticity of demand is similar for PV and non-PV households, ranging from -0.14 to -0.10. When considering the previously defined PV sizing categories, results reveal that in the baseline pre-solar period Net Export households exhibit the largest response to changes in price, while Net Import households are the most inelastic. Non-PV and Net Zero households are observed to have similar responsiveness to changes in electricity price.

We next estimate electricity demand utilizing both pre- and post-solar installation data spanning the entire study period from January 2000 to May 2016. Household responsiveness to price and weather variations is found to differ before and after installation of solar PV systems. Following PV installation, household consumption becomes more sensitive to price variation, estimated between -0.25 and -0.17. Clear differences are also observed between the various PV sizing groups in both their pre-solar responses to price and the impact of installation on their price response. Electricity consumption in Net Import and Net Zero households becomes more elastic to price variations following PV installation. Conversely, Net Export households become less responsive to price after installation of “over-sized” PV systems. This latter observation is not entirely surprising when considering that Net Export households typically have an excess of electricity at the end of each billing period. This natural excess in electricity produced versus electricity demanded provides them sufficient overhead to alter their consumption without concern for energy price fluctuations.

Results also demonstrate a statistically significant effect of weather on residential electricity consumption. Temperature is found to have a strong positive correlation with energy consumption levels. After solar installation, we find that PV households become more sensitive to weather variations, especially to changes in temperature. This observation mirrors the earlier descriptive evidence shown in figure G.2, suggesting increased variations in electricity consumption between summer and winter months among PV households.

The remainder of the paper is organized as follows. Section 3.2 reviews literature related to this study. Section 3.3 describes the proprietary dataset underlying the presented analysis and details how each variable was processed. Section 3.4 and 3.5 introduce PV sizing categories and present summary statistics and descriptive evidence for the data. Section 3.6 details the econometric methodology used in the analysis, with estimation results reported in Section 3.7. Finally, Section 3.8 offers concluding remarks and additional discussion of the results.

3.2 Literature Review

There is an extensive literature pertaining to demand for electricity that utilizes a wide variety of econometric estimation methods including time series analysis, partial adjustment model (PAM), generalized methods of moments (GMM), and ordinary least square estimation (OLS). Table F.1 presents a summary of the existing electricity demand studies in the literature. There is as yet no clear consensus as to which methodology is most appropriate for electricity demand analysis. These studies typically incorporate similar control variables, including income, weather, demographic and dwelling characteristics, while employing different estimation procedures. These variations can be attributed to the studies' differing in their length of time covered by the sample, demand sectors, types of data, and specification of prices. Despite these underlying differences, the vast majority of studies find price elasticity of electricity demand to be inelastic.

A common challenge when evaluating the relationship between electricity consumption and price variations is the endogeneity problem.[26] Prior studies have generally assumed residential households to be price takers since their electricity consumption behavior has little to no effect on changes in electricity prices (Halvorsen and Larsen 1999; Shi et al. 2012). This study utilizes disaggregated household-level data and a flat electricity price in Hawai'i. Therefore, we can assume each residential household to be a price taker, thereby avoiding the endogeneity problem in our electricity demand model.

Within this study, we employ a fixed effects model with the log-log functional form to assess residential electricity demand. The fixed effects model controls for the impact of weather variation through the inclusion of temperature, wind speed, and rainfall variables. The impact of weather on electricity consumption has been widely studied in the literature (Kamerschen and Porter 2004; Filippini 2011). In the residential sector, several studies have found that temperature is a major determinant of household electricity demand (Silk and Joutz 1997; Hondroyiannis et al. 2002). Other climatic variables including wind speed and humidity have been used as

[26] Besides price endogeneity, another problem arises since PV installation is endogenous. Due to data limitation, however, we are not able to find variables that can serve as valid instruments, leading to bias in the price elasticity estimates.

correcting terms for the influence of temperature in energy consumption analyses (Engle et al. 1992; Li and Sailor 1995; Cancelo et al. 2008; Yan 1998).

In addition to the aforementioned electricity demand model, this study also explores whether solar adoption leads to changes in electricity consumption behavior. A number of previous studies have referred to such a change in electricity consumption behavior as the solar "rebound" and "double-dividend" effects (McAllister 2012; Blackburn 2014; Deng and Newton 2016). The notion of rebound effects has been extensively examined and reviewed in the energy efficiency literature (Khazzoom 1980; Khazzoom 1987; Greening et al. 2000; Sorrell 2007: Sorrell et al. 2009). The rebound effect as outlined in these studies arises when energy consumption increases as a result of improvements in energy efficiency. The direct rebound effect can be decomposed into distinct income and substitution effects (Greening et al. 2000; Gillingham et al. 2015). The income effect reflects the decrease in the cost of energy services leading to an increase in households' real income and increased consumption of alternative goods as a result of energy efficiency improvements. The substitution effect captures the increase in energy consumption in response to a change in relative prices. Conversely, the "double-dividend" effect leads to increased conservation following adoption of energy efficiency measures.

Unlike other energy efficient appliances, PV systems are not energy consuming devices. However, solar PV systems can considerably reduce electricity costs, theoretically incentivizing households to consume more energy. There is as yet no clear consensus in the literature regarding how the adoption of PV alters household consumption behavior. Employing questionnaire data, Keirstead (2007) finds that there exists a solar "double-dividend" effect among residential households following installation of PV systems. The author also finds that PV adoption significantly improved awareness of both electricity consumption and generation. However, this conclusion is drawn based on self-reported information and could, therefore, be misleading.

Several studies have examined the role that pre-solar usage plays in predicting the effects of solar adoption. Haas et al. (1999) find that solar adoption triggers increased levels of energy conservation among high electricity consumers in Austria. High energy users in the aforementioned study decreased their consumption after PV installation, while low energy users showed a slight increase in energy demanded. Blackburn (2014) examined post-solar consumption behavior and installation experience via survey and consumption data of residential households in Texas, finding significant solar "rebound" and "double-dividend" effects arising after PV installation.

In addition, McAllister (2012) leverages consumption and installation data of 5,243 Californian households with solar PV to assess the impact of installing a solar system on electricity consumption. The author examines patterns for system sizing and theorizes that grouping PV customers on the basis of their pre-solar energy use would lead to a better understanding of post-solar consumption behavior. The results of McAllister's study show that the majority of PV systems in the sample dataset were sized to offset approximately 20% to 80% of households' total energy demand. Only 10% of the observed households were found to size their PV systems to displace more than 100% of their pre-solar energy consumption. The author employs the sizing categorization to evaluate the correlation between sizing decision and post-solar consumption. The results indicated that PV households with "under-sized" systems relative to their pre-solar usage tend to demonstrate decreased consumption following installation, whereas those with larger systems were more likely to increase their level of consumption.

Although these prior studies revealed changes in consumption patterns pre- and post-solar adoption, no comparison between PV and non-PV adopters was undertaken. Our study aims to fill this gap in the literature by not only comparing energy usage patterns between pre- and post-solar installation but also comparing consumption among PV and non-PV households.

3.3 Data Summary

3.3.1 Data Processing

In this study, we employ the same underlying data set from Hawaiian Electric Company (HECO) utilized in Chapter 2 while incorporating additional electricity price and climatic variables. Following Ito (2014), it is hypothesized that consumers respond to average price.[27] Average residential electricity price in this study was provided by the U.S. Energy Information Administration (EIA) and Department of Business, Economic Development and Tourism (DBEDT). To adjust the electricity price for inflation, the nominal electricity price was divided

[27] Given the flat electricity pricing structure in Hawaii, marginal price is equal to the average price for consumers.

by the Consumer Price Index (CPI) for all urban consumers (all items) and then multiplied by the annual average of 2015.[28] This adjustment has the effect of normalizing all electricity prices to 2015 dollar values. To account for the effect of weather variation on electricity consumption, the monthly maximum temperature (Fahrenheit), average wind speed (miles per hour) and total precipitation (inches) were obtained from the National Weather Service (NWS) for Honolulu International Airport weather station.

We also determine, for each PV household, whether additional PV systems have been added to their accounts during the observed time period. It is crucial to validate whether PV customers have additional installed systems in order to accurately calculate their gross electricity consumption and determine their appropriate sizing category. Additional information detailing the number of add-on systems, their size, and the date of installation for each additional system was added using HECO's internal data portal. From this process, 397 PV accounts were identified which had installed at least one additional PV system after the initial PV installation. Such accounts were excluded from our analysis, leaving 2,093 PV and 1,557 non-PV households remaining in the sample data set.[29]

Next, monthly solar electricity produced by rooftop PV is estimated. Let I_{it} be the solar irradiance measured at a household i at time t (Watt/m^2) and S_i be a PV system size of a household i. The estimated monthly solar electricity produced by a rooftop PV for a household i at time t (E_{it}) is calculated as:

$$E_{it} = I_{it*} S_i \tag{3.1}$$

To accurately estimate PV energy output over the course of a solar system's lifespan, we apply a 0.06% degradation rate per month to the estimated PV energy production (Jordan and Kurtz 2013). Let α be the number of months after the month of PV installation, then the degraded PV energy output of a household i at time t (DE_{it}) is calculated as:

$$DE_{it} = E_{it*}(1.0006)^{-\alpha} \tag{3.2}$$

[28] Source: Consumer Price Index for All Urban Consumers: All items in Honolulu, HI (MSA), Federal Reserve Bank of St.Louis.
[29] PV households with additional PV systems installed were excluded from this study to assure that none of the PV households have transitioned from one PV sizing group to another during the study period.

In order to calculate gross electricity consumption, it is necessary to identify the month in which the new PV panels become operational. The installation date referenced in the dataset refers to the date of approval of the interconnection agreement submitted by the customer and does not always represent the actual date of installation. To mitigate this issue, we identify the first subsequent month in which a significant reduction in net monthly consumption is detected. These observations are then used to revise the installation date of each PV customer accordingly.

Gross electricity consumption is calculated by adding the degraded monthly PV energy output (DE_{it}) to net electricity consumption:

$$GkWh_{it} = NkWh_{it} + DE_{it} \tag{3.3}$$

where $GkWh_{it}$ and $NkWh_{it}$ are gross and net electricity consumption of a household i at time t, respectively. Although we previously adjusted the actual installation date to better reflect the time of installation, three additional observations – one month before, one month after and the estimated actual month of installation – are excluded for each customer to ensure clean pre- and post-solar consumption measurements.

3.3.2 Summary Statistics

Two distinct study datasets, baseline and overall, are considered in the analysis. The baseline dataset spans the period from January 2000 to December 2009 and excludes observations occurring after PV installation for each household. The overall dataset consists of all observations, both pre- and post-solar, from January 2000 to May 2016. Analysis of the baseline dataset is used to illustrate the starting point of households in each customer group, whereas analysis of the overall dataset enables us to assess the impact of PV adoption on household electricity consumption.

Table F.2 shows summary statistics of monthly electricity consumption. Comparing consumption of non-PV and PV households during the pre-solar period (2000-2009), it is observed from table F.2 that households who are more likely to install PV consume more electricity than those who are less likely to install PV. When comparing pre- and post-solar installation over the whole study period (January 2000 – May 2016), residential single-family households with PV use less electricity on average after PV installations.

Net usage represents the difference in electricity bought and sold by a household. At the conclusion of each billing period, households pay the utility for their net electricity usage. A negative net usage value represents the amount of energy credit a PV household receives from the utility. Households with negative net energy usage only pay the minimum surcharge. It is observed in table F.2 that for PV households, post-solar net electricity consumption is substantially lower than gross electricity usage, with a minimum of -2,240 kWh.

Table F.3 shows summary statistics for the set of control variables including electricity price, solar PV system size in kilowatt (kW), and various climatic variables. In the next section, the subcategorization of PV households on the basis of their PV sizing decisions and associated descriptive evidence is presented.

3.4 PV Sizing Decisions

Potential PV customers are faced with a number of necessary steps when first adopting solar. In order to identify the PV system size that best fits their needs, a household must first analyze their present electricity consumption along with any future projected increases or decreases in electricity demand. For example, a household may be planning to purchase an electric vehicle (EV) and install a home EV charger, leading to increased electricity usage. If the aforementioned household's goal is to cover 100% of their electricity requirements using solar energy then an "over-sized" PV system may be desirable when taking into account their anticipated consumption increase. In contrast, if a household anticipates reduced electricity demand in the future then a smaller PV system may be more appropriate to meet their needs.

Prospective PV adopters must also choose a PV energy production goal to offset their electricity usage. While some homeowners elect to install PV systems that offset 100% of their grid electricity demand, others opt for smaller systems with lower energy offset percentage in order to reduce the cost of solar installation and accelerate return on investment. Policies and associated regulations may also serve to influence households' solar sizing decisions. In California, for example, utilities do not compensate systems larger than the electricity used by a household in the previous year. Therefore, households are typically limited to PV system sizes that offset no more than their annual onsite electricity load. McAllister (2012) found that the solar energy generated by PV adopters canceled out the higher-tiered-rate charges each month, leaving PV adopters with only the baseline rate to pay. These PV households are therefore better off financially with the lower percentage energy offset.

In Hawai‘i, no such regulations have been implemented, although there is a system capacity limit of 100 kW for Net Energy Metering (NEM) program customers. NEM customers are allowed to return all of their excess energy produced by PV systems to the grid, receiving full retail rate credit to their account. In addition, these energy credits may be carried over to the next month if unused. At the conclusion of each 12-month reconciliation period, any unused credits remaining in a NEM customer's account are zeroed out and the process begins again. These generous compensation policies incentivize PV customers in Hawai‘i to install larger-than-necessary solar systems.

In the ensuing section, we analyze customers' solar sizing decisions to determine whether the "over-sizing" PV installation trend actually exists in Hawai‘i. The rational choice for a prospective PV household is to choose a PV system size that not only minimizes their payback period, but also maximizes the utility of any planned future energy consumption. "Optimal" system size can, therefore, vary greatly between different households depending on their 12-month pre-solar electricity consumption and anticipated future needs. "Optimal" PV system size is also dependent on a variety of other factors such as shading obstruction, roof condition, available rooftop space for PV module placements, the orientation and tilt of the system, solar resource availability, and financial considerations.[30] High temperatures also negatively affect solar panel efficiency, and can significantly lessen PV energy production (Skoplaki and Palyvos 2009). This decrease in efficiency is due to the fact that as the temperature of a PV panel rises; its output current increases exponentially, linearly reducing voltage output.

After taking all of these factors into account, we define the "optimal" solar system size as the one designed to offset, at most, 100% of a household's average 12-month pre-solar electricity usage. Given a customer's preceding 12-month of electric bills prior to solar installation, and the available sunlight at the proposed array site, we apply a rule of thumb for calculating the "optimal" PV system size for a given household i (OS_i) as follows:

[30] Households' decision to size rooftop PV may also be impacted by outside factors. For example, solar contractors and installers may influence a household's PV sizing decisions by suggesting a larger or smaller system than is financially optimal.

$$OS_i = \frac{Pre_i}{CF * 24 * 31} \tag{3.4}$$

where Pre_i is an average of monthly kWh that household i consumed during the 12 months prior to PV installation. Solar Capacity Factor (*CF*) is the ratio of actual power generation over a given time period and the installed (nameplate) capacity of the solar PV system.

Examining 2013 and 2014 data, monthly *CF* for Oahu ranges from 13.2% to 22.7%, with an average of 18.4%.[31] Instead of using the average value of *CF*, the maximum and minimum CF values are employed to calculate the "optimal" size band. The lower ($\underline{OS}_i$) and upper ($\overline{OS}_i$) bounds of the band of a household i are calculated as follows:

$$\underline{OS}_i = \frac{Pre_i}{0.227 * 24 * 31} \tag{3.5}$$

$$\overline{OS}_i = \frac{Pre_i}{0.132 * 24 * 31} \tag{3.6}$$

The lower and upper bounds represent the effect of seasonal variations in weather, solar resource, and household electricity demand. The "optimal" size band varies amongst households depending on their 12-month pre-solar average usage. PV households are categorized on the basis of where they are located relative to the "optimal" size band. PV households are categorized as Net Zero if their PV system size falls within the band. Those with rooftop PV system larger than the upper bound of the band are categorized as Net Export, while those with PV systems smaller than the lower bound are categorized as Net Import. From a sample of 2,093 residential single-family households with solar PV, we find that approximately 2% of households are categorized as Net Export, 41% as Net Import, and the remaining 57% as Net Zero.

Household percentage energy consumption offset is calculated based on 12-month average pre-solar electricity consumption and PV energy output. Figure G.3 shows that on average PV households belonging to the Net Import group sized their rooftop PV systems to displace approximately 59%, PV households belonging to the Net Zero group sized their rooftop PV systems to displace approximately 106%, and PV households belonging to the Net Export group

[31] Source: HECO

sized their rooftop PV systems to displace approximately 163% of their electricity consumption by their PV systems. The installation trend for households within each sizing group is shown in figure G.4. It is observed that the majority of earlier adopters were classified as Net Import households, with a small number of Net Zero households.

The relationship between households' pre-solar electricity consumption and their choice of solar PV system is further examined in figure G.5. It compares 12-month pre-solar monthly usage of PV households across the aforementioned sizing groups, illustrating that Net Import households consume more electricity, while Net Export households consume less. Figure G.6 examines the distribution of solar system size for the different PV sizing categories. We find that Net Import households installed smaller PV systems relative to the other groups, with Net Zero and Net Export households having similar PV system size distribution. These two figures reveal that PV households who "over-sized" their solar systems did not necessarily install significantly larger systems than households in the other groups, but rather consume less electricity relative to the size of their PV system.

Table F.4 reports summary statistics of households' electricity consumption in each customer group using both the baseline and overall datasets. In the overall dataset, the average net monthly usage of Net Export households is observed to be negative. This indicates that the amount of energy returned to the grid by these households exceeds that which they purchase from the utility, resulting in minimum electric bills following PV installation.

3.5 Consumption Trend

Figure G.7 depicts average annual electricity usage and percent year-over-year change, delineating differences in energy consumption patterns amongst PV and non-PV households within each sizing group. It is observed that there exists a slight difference in consumption levels between the different customer groups, with Net Export households being the lowest energy users and Net Import households the highest.

In observing the percent year-over-year change in figure G.7, we see that Net Export households exhibit a larger decline in energy demand in the period between 2004 and 2011. However, after 2011 their usage significantly increases as the percentage of customers with PV within the sizing group increases. The largest decline in consumption for Net Import households is observed in 2012, corresponding with the sharp rise in electricity prices in 2011

The next section will further investigate whether there is an observable “rebound” or “double-dividend” associated with PV installations by analyzing changes in energy consumption behavior of PV households before and after PV adoption.

3.5.1 Comparisons: Pre-Solar VS Post-Solar Consumption Behavior

In order to analyze household consumption behavior before and after PV installation, a solar time trend, measuring solar gross electricity consumption in the two years pre-solar and four years post-solar, is constructed. Figures G.8 and G.9 illustrate average trends in electricity consumption for PV and non-PV households. We observe that non-PV households lower their electricity use, but at a gradually decreasing rate. This decreasing trend in electricity consumption may result from a change in energy use behavior in response to price and/or weather variations and/or home energy efficiency improvements.[32] Given the limited information on energy efficiency efforts made by households in our dataset, we are unable to parse their impact on household electricity consumption. However, it is probable that the declining trend in energy use among non-PV households is due largely in part to increased energy efficiency saturation.

Figure G.9 shows that, on average, PV households increase their energy consumption after PV installation. Comparing electricity consumption pre- and post-installation, we observe a 3% increase in the first year following PV installation. The rate at which electricity consumption increases for these households falls in ensuing years after this initial jump. This observation implies that although PV customers adjust their electricity consumption behavior in the period immediately after PV adoption, the overall impact of this rise is muted by the subsequent decline in the years following.

Figures G.8 and G.9 also show significant differences in post-solar consumption trends among households belonging to each PV sizing category. When compared to their 12-month pre-solar usage, Net Import households consume 4% less electricity in the first year post-installation. Net

[32] In June 2009, Hawai‘i established its Energy Efficiency Portfolio Standard (EEPS) setting a goal of electricity reduction by 4,300 gigawatt-hours (GWh) by 2030. Hawai‘i EEPS has successfully accelerated energy efficiency resources deployment. Source: www.dsireusa.org

Import households have an average percent energy offset of 59%, meaning that even after solar installation they are still left with positive electric bills. Therefore, after solar installation, these households may elect to modify their consumption behavior and/or adopt other home energy efficiency improvements to further conserve energy. Doing so enables their solar system output to cover a higher percentage of their overall demand, thereby reducing the cost of electricity and accelerating the return on investment of their PV installation.

Net Zero households increase their energy usage by approximately 8% after PV installation. However, this consumption trend declines in subsequent years, indicating a slight adjustment to their electricity consumption behavior follow PV installation.

In contrast to the other two PV sizing groups, Net Export households demonstrate a clear increasing trend in post-solar energy usage. The post-solar consumption of Net Export households increases by over 30% on average in the first year following PV installation, and further increases each year thereafter. It is not altogether surprising that Net Export households with “over-sized” PV systems increase their energy use following installation. Some of these households may have planned to increase their energy usage due to an anticipated change in their needs, such as the purchase of an EV. Moreover, the excess energy produced by “over-sized” PV systems may be perceived as “free”. Having a substantial electricity surplus and paying only the minimum surcharge on their monthly electric bills, Net Export households have considerable incentive to increase their consumption after PV adoption.

Our descriptive evidence further reinforces earlier findings by McAllister (2012) that households with “under-sized” PV systems tend to decrease their energy consumption, while those with “over-sized” PV systems tend to increase their energy consumption after PV installation. As in these previous studies, we have observed that solar “rebound” and “double-dividend” effects among PV adopters are highly correlated with their sizing decisions.

3.6 Statistical Model

The ensuing section evaluates the relationship between residential electricity demand and its relevant influencing factors for 3,650 households – 1,557 non-PV and 2,093 PV adopters – on Oahu, Hawai‘i. We hypothesize that residential electricity demand is dependent on the price of electricity, weather variation and seasonal patterns, the business cycle, household demographic and socioeconomic characteristics, and PV installation. The general electricity demand model can be represented by the following function:

$$Y_{it} = f(P_{t-1}, \text{Weather}_t, \text{Seasonal Trend}_t, \text{Business Cycle}_t, PV_{it}, X_i) \tag{3.7}$$

where Y_{it} is household i's electricity consumption in kWh at month t. The variable PV_{it} indicates the time t at which household i installed PV. P_{t-1} is average residential electricity price in cents per kWh at time t-1. Given that households typically receive price information in their electric bills at month's end, we hypothesize that the previous month's electricity price dictates their electricity consumption decisions in the subsequent month. The effect of weather variation is controlled by including maximum temperature, average wind speed and total precipitation in the regression model. Household characteristics and demographics (X_i) are accounted for using household fixed effects. The impact of seasonality and the business cycle on residential electricity usage is captured via month and year fixed effects.

Based on equation (3.7), we employ a log-log functional form to model residential electricity demand. We first estimate the "baseline" energy consumption of PV and non-PV households from January 2000 to December 2009, excluding post-installation observations. Formally, we posit the following empirical baseline (pre-solar) model:

$$\begin{aligned} \ln(Y_{it}) \quad = \quad & \beta_0 + \beta_1 \ln(P_{t-1}) + \beta_2 \ln(P_{t-1})\, PV_i \\ & + \beta_3 \ln(Temp_t) + \beta_4 \ln(Wind_t) + \beta_5 \ln(Rain_t) \\ & + \beta_6 \ln(Temp_t)\, PV_i + \beta_7 \ln(Wind_t)\, PV_i + \beta_8 \ln(Rain_t)\, PV_i \\ & + \gamma_i + u_m + v_y + \varepsilon_{it} \end{aligned} \tag{3.8}$$

The baseline model in equation (3.8) captures underlying differences in consumption of residential PV and non-PV customers in the period before PV installation, along with the impact of weather fluctuations on their respective energy usage. The PV dummy variable, PV_i, is set equal to 1 if household i is observed to have installed a PV system at any time during the study period, and equal to 0 if it did not. Three climatic variables are included in the electricity demand model: (1) maximum temperature measured in degrees Fahrenheit ($Temp_t$); (2) average wind speed in miles per hour ($Wind_t$); and (3) total precipitation in inches ($Rain_t$). Relevant household characteristics are controlled for using household fixed effects (γ_i). Month and year dummy variables, u_m and v_y, capture the impact of seasonal factors and the business cycle on electricity consumption.

To determine the impact of solar adoption on consumption we utilize a post-solar dummy variable (τ_i), which is set equal to 1 for periods following solar adoption and 0 otherwise, for a given household *i*. We theorize that PV adoption not only influences the manner in which residential households alter their consumption in response to changes in price, but also their sensitivity to weather variations. Data for the entire study period (January 2000 – May 2016), including both pre- and post-solar observations, is used to estimate our overall (pre- and post-solar) demand model which can be expressed as:

$$\begin{aligned}\ln(Y_{it}) \quad = \quad & \beta_0 + \beta_1 \ln(P_{t-1}) + \beta_2 \ln(P_{t-1})\, PV_i + \beta_3 \ln(P_{t-1})\, PV_i\, 1(t>\tau_i) \\ & + \beta_4 \ln(Temp_t) + \beta_5 \ln(Wind_t) + \beta_6 \ln(Rain_t) \\ & + \beta_7 \ln(Temp_t)\, PV_i + \beta_8 \ln(Wind_t)\, PV_i + \beta_9 \ln(Rain_t)\, PV_i \\ & + \beta_{10} \ln(Temp_t)\, PV_i\, 1(t>\tau_i) + \beta_{11} \ln(Wind_t)\, PV_i\, 1(t>\tau_i) + \beta_{12} \ln(Rain_t)\, PV_i\, 1(t>\tau_i) \\ & + \gamma_i + u_m + v_y + \varepsilon_{it} \qquad (3.9)\end{aligned}$$

The sizing of solar PV systems is captured by replacing the PV dummy variable (PV_i) in equation (3.8) and (3.9) with sizing group dummy variables. Let NI_i, NZ_i, NE_i equal 1 for household *i* if it belongs to the Net Import, Net Zero or Net Export sizing groups, respectively, and 0 otherwise. Upon replacing the PV dummy variable in this manner, our model of baseline consumption by sizing group is:

$$\begin{aligned}\ln(Y_{it}) \quad = \quad & \beta_0 + \beta_1 \ln(P_{t-1}) + \beta_2 \ln(P_{t-1})\, NI_i + \beta_3 \ln(P_{t-1})\, NZ_i + \beta_4 \ln(P_{t-1})\, NE_i \\ & + \beta_5 \ln(Temp_t) + \beta_6 \ln(Wind_t) + \beta_7 \ln(Rain_t) \\ & + \beta_8 \ln(Temp_t) NI_i + \beta_9 \ln(Wind_t)\, NI_i + \beta_{10} \ln(Rain_t)\, NI_i\end{aligned}$$

$$+ \beta_{11} \ln(Temp_t)NZ_i + \beta_{12} \ln(Wind_t) NZ_i + \beta_{13} \ln(Rain_t) NZ_i$$

$$+ \beta_{14} \ln(Temp_t)NE_i + \beta_{15} \ln(Wind_t) NE_i + \beta_{16} \ln(Rain_t) NE_i$$

$$+ \gamma_i + u_m + v_y + \varepsilon_{it} \qquad (3.10)$$

and the resulting overall consumption by sizing group model is:

$$\begin{aligned}
\ln(Y_{it}) \quad = \quad & \beta_0 + \beta_1 \ln(P_{t-1}) + \beta_2 \ln(P_{t-1}) NI_i + \beta_3 \ln(P_{t-1}) NZ_i + \beta_4 \ln(P_{t-1}) NE_i \\
& + \beta_5 \ln(P_{t-1})NI_i \, 1(t>\tau_i) + \beta_6 \ln(P_{t-1}) NZ_i \, 1(t>\tau_i) + \beta_7 \ln(P_{t-1}) NE_i \, 1(t>\tau_i) \\
& + \beta_8 \ln(Temp_t) + \beta_9 \ln(Wind_t) + \beta_{10} \ln(Rain_t) \\
& + \beta_{11} \ln(Temp_t)NI_i + \beta_{12} \ln(Wind_t) NI_i + \beta_{13} \ln(Rain_t) NI_i \\
& + \beta_{14} \ln(Temp_t)NZ_i + \beta_{15} \ln(Wind_t) NZ_i + \beta_{16} \ln(Rain_t) NZ_i \\
& + \beta_{17} \ln(Temp_t)NE_i + \beta_{18} \ln(Wind_t) NE_i + \beta_{19} \ln(Rain_t) NE_i \\
& + \beta_{20} \ln(Temp_t) NI_i \, 1(t>\tau_i) + \beta_{21} \ln(Wind_t) NI_i \, 1(t>\tau_i) + \beta_{22} \ln(Rain_t) NI_i \, 1(t>\tau_i) \\
& + \beta_{23} \ln(Temp_t) NZ_i \, 1(t>\tau_i) + \beta_{24} \ln(Wind_t) NZ_i \, 1(t>\tau_i) + \beta_{25} \ln(Rain_t) NZ_i \, 1(t>\tau_i) \\
& + \beta_{26} \ln(Temp_t) NE_i \, 1(t>\tau_i) + \beta_{27} \ln(Wind_t) NE_i \, 1(t>\tau_i) + \beta_{28} \ln(Rain_t) NE_i \, 1(t>\tau_i) \\
& + \gamma_i + u_m + v_y + \varepsilon_{it} \qquad (3.11)
\end{aligned}$$

3.7 Empirical Results

3.7.1 No-PV & PV

Baseline Model – Pre-Solar Period (January 2000 – December 2009)

We first estimate electricity demand of residential households with and without PV. Empirical results in specification (1) of table F.5 demonstrate that both PV and non-PV households are price-inelastic in the pre-solar period. Their respective price elasticities of electricity demand are both found to fall between -0.12 and -0.10. This implies that, ceteris paribus, a 10% increase in price is estimated to result in approximately a 1% to 1.2% decrease in total energy consumption

It is also found that wind speed and precipitation have a statistically significant, albeit small impact on household electricity consumption. As anticipated, the coefficient of temperature is positive and statistically significant, indicating that households consumed more electricity as temperature increased during the pre-solar period. PV households were found to be more responsive to temperature variations than were non-PV households.

Overall Model – Pre & Post-Solar Period (January 2000 – May 2016)

We next examine the effects of PV installation over the whole study period including both pre- and post-installation observations. Results detailed in specifications (2) and (3) of table F.5 reveal that PV households become slightly more sensitive to variations in price and weather after solar installation, with the post-solar price elasticities of PV households estimated between -0.25 and -0.17. Specification (3) of table F.5 reflects additional controls for the impact of weather on post-solar electricity consumption. Empirical results under this analysis indicate that the effect of an increase in temperature differs significantly for households before and after PV installation. For PV households, a 10% increase in temperature results in a 0.6% increase in electricity consumption before solar adoption, and a 13.8% increase in electricity consumption following solar adoption.

3.7.2 No PV & PV by Sizing Group

Baseline Model – Pre-Solar Period (January 2000 – December 2009)

Initial sizing decisions are also shown to be a predictive factor of electricity consumption for PV households. Regression results presented in table F.6 indicate that non-PV and Net Zero households demonstrate similar price elasticities in the pre-solar period, while households that install “over-sized” PV systems are the most price-elastic. These results suggest that prior to PV installation; Net Export households are more sensitive to price variations relative to those households belonging to other sizing categories. The choice to install “over-sized” PV systems, capable of producing more electricity than they typically require, therefore provides them with a buffer against unexpected price fluctuations.

Net Import households, although found to be the most responsive to weather variations, are observed to be the least responsive to price. Intuitively, these households may have been more disciplined than others in regards to their electricity usage, meaning that changes to electricity price have minimal impact on their consumption. Due to this dynamic, there was little need for them to “over-size” their PV systems to offset electricity demand levels exceeding their normal use-state.

Overall Model – Pre & Post-Solar Period (January 2000 – May 2016)

Specifications (5) and (6) of table F.6 demonstrate that Net Import and Net Zero households become more responsive to changes in price after solar adoption. The price elasticities of demand for Net Import households are found to change from -0.01 to -0.18 post-solar, while the price elasticities of demand for Net Zero households are found to change from -0.09 to -0.22, during the pre- and post-solar periods, respectively. These changes in price sensitivities suggest that PV adoption leads to increased awareness of electricity demand amongst Net Import and Net Zero households.

Empirical results reveal that although the estimated price elasticity of Net Export households who “over-sized” their PV systems become less negative, it is not a statistically significant change. This result is not altogether surprising, as the PV installations of these households are sized to offset considerably more energy than they typically require. Unlike PV households in other sizing categories, Net Export households are able to consume more electricity without increasing their monthly electric bill beyond the minimum monthly surcharge.

Results to this point have demonstrated that PV adoption triggers a significant improvement in energy use awareness, leading to a corresponding change in consumption behavior. Due to the high cost of solar installations, many households attempt to maximize their return on investment by modifying their consumption behavior. Moreover, these same households are more attentive to other factors relating to their post-solar consumption including electricity price, the performance of their PV systems, the amount of energy credits carried over from the previous month, and variations in weather and solar resources. Prior studies on the impact of PV installation have also noted an increase in electricity use awareness amongst PV adopters (Keirstead 2007; Rai and McAndrews 2012). Although data availability limits our ability to fully explain the underlying motivators of this increase in awareness, we have nonetheless shown marked changes in consumption behavior before and after solar installation within both the presented descriptive evidence and empirical analysis.

3.7.3 Additional Findings

Our results have indicated that the majority of households in the study sample chose to size their PV systems to offset roughly 100% of their pre-solar average electricity consumption. However, these findings were based on observations of customers provided with adoption incentives through the NEM program. In October 2015, the Hawai‘i Public Utilities Commission issued a ruling ending NEM for all new customers. At present, the Hawaiian Electric Company offers customers two new types of tariffs, consumer self-supply (CSS) and consumer grid-supply (CGS). The CSS tariff does not enable PV customers to send excess energy generated back to the grid and any exported energy is not compensated by the utility. The CGS tariff more closely resembles the now defunct NEM program, excepting that CGS pays customers a reduced price for excess energy exported to the grid. These policy changes increase the opportunities for new technologies and business models leveraging battery storage and demand flexibility, which provide customers with greater flexibility and enable them to better respond to changing grid conditions.

Under the newly introduced CSS and CGS tariffs, PV customers are no longer as incentivized to “over-size” their rooftop PV systems as they were under NEM. Due to the drastically decreasing value of exported energy, “over-sizing” PV systems results in a higher initial PV installation cost without the corresponding return on investment provided under NEM. This change in individual household incentives may, however, result in increased overall social welfare since the combination of households with “over-sized” systems and PV penetration limits imposed by the utility have deprived many new households of the opportunity to install rooftop solar.

According to the Kaua‘i Island Utility Cooperative and the Hawaiian Electric Companies, the typical household consumes approximately 25% of its electricity between 9 a.m. and 3 p.m. The previously discussed PV sizing calculation can be modified based on daytime pre-solar energy usage of households in our sample. We assume that a “*daytime right-sized*” PV system is one designed to offset roughly 25% of a household's average pre-solar consumption.[33] Following this adjustment, 95% of households in the study sample are categorized as Net Export and fewer than 2% of households are categorized as Net Import. This result implies that the majority of NEM customers export excess PV energy to the grid during daytime hours.

Based on our "*all-day right-sized*" PV sizing category discussed in section 3.4, figure G.10 displays the proportion of exported energy relative to overall estimated PV energy output. The average PV household exports approximately 59% of their PV energy output to the grid, with Net Export households being the highest at 67% on average.[34] Monthly energy costs for NEM households reflect the difference between the amount of electricity that they purchase from the utility, and the amount that they sell back to the grid. Figure G.11 illustrates the distribution of net monthly energy usage of PV households broken down by PV sizing group. It is observed that Net Export households typically exhibit negative net usage, under which they are only responsible for paying the monthly minimum surcharge, with any excess energy credits carrying over to the next month.

These results suggest that there is no economic benefit for customers to "over-size" their solar PV and over-produce electricity under CGS due to the limited compensation received for excess energy produced and the inability to carry credits over to the next month. Due to this, it is crucial for CGS customers to "right-size" their PV systems in order to maximize their return on investment.

3.8 Conclusion and Discussion

To better understand the true impact of solar PV adoption on electricity consumption, a rigorous analysis using disaggregated data is required. This study first examined how PV and non-PV customers alter their energy usage over time. Findings indicated that PV adoption has a significant impact on household electricity consumption, with the majority of PV households found to increase their electricity consumption following installation while at the same time non-PV households were decreasing their electricity demand.

[33] The calculation for PV sizing is the same as that mentioned in section 3.4, but each household's average pre-solar consumption is reduced to 25%.
[34] Net Zero and Net Import households export approximately 55% and 64% of their PV energy output to the electric grid, respectively.

PV households were categorized on the basis of their PV sizing decisions, enabling a more granular examination of their pre- and post-solar consumption trends. This analysis revealed the presence of both solar "rebound" and "double-dividend" effects in the study sample. Households with "under-sized" PV systems were found to consume less, whereas those with "right-sized" or "over-sized" were found to consume more electricity following solar installation.

Changes to household electricity consumption in response to price and weather variations were also examined. An empirical study of consumption data revealed that customers became more sensitive to such variations post installation. Households with "over-sized" PV systems were more price-inelastic, while households belonging to the other two sizing groups were more price-elastic following solar installation. Temperature was found to have a stronger positive impact on residential electricity demand following PV installations, leading to increased variation in consumption between summer and winter months.

Although the NEM program was ended in the last quarter of 2015, the majority of current PV customers in Hawaiʻi are grandfathered under the NEM tariff conditions. It is therefore essential to understand behavioral patterns of NEM customers in spite of the program ending. Our findings provide valuable insights, from both utility and policy perspectives, into how changes in price may alter household electricity usage following PV adoption. As electricity consumption behavior encompasses both the overall quantity of electricity used and the time of day at which it was consumed, analyses leveraging time-of-day consumption data will shed light on possible load shifting and the potential benefits of battery storage technologies.

Results clearly demonstrated that "over-sizing" PV discourages energy conservation in households. The shift from NEM to CSS and CGS tariffs can be therefore viewed as an important policy shift, with the newly enacted tariffs designed to encourage "right-sizing" amongst new PV customers. However, CSS and CGS customers are unlikely to behave similarly to NEM customers, making continued study of customers' consumption behavior under these new pricing structures vital to the design of effective policies and incentive programs.

Appendix A

Tables for Chapter 1

Table A.1: Summary Statistics of Variables at Distribution Transformer Level.

Variables		**Mean**	**SD**	**Min**	**Max**
Variations (SD) in Net Electricity Load (kW)[a]		270.9	213.4	3.1	1,800.5
Daytime (Net) Minimum Load (kVA)		2,230.4	896.1	108	4,412.2
Customer Mix	Total Number of Customers	1,790.9	1,150.2	45	5,459
	Number of Residential Customers	1,606.0	1,125.1	0	5,256
	Number of Commercial Customers	184.9	124.4	7	520
	Percentage of Residential Customers (%)[b]	79%	29%	0	99%
Weather	Average Temperature (Celsius)	24.4	3.1	16.8	31.6
	Average Humidity (%)	71%	9%	48%	88%
	Average Wind Speed (mph)	7.8	2.6	3.00	13
	Average Solar Irradiance (unitized 0-1)	0.2	0.3	0	0.9
Solar Capacity	PV Installed Capacity (kW)[c]	631.9	658.4	0	4,756.4

[a] Net load is defined as the amount of electricity met by utility generation, covering a period from September 2010 to May 2014

[b] Percentage of residential customers is calculated by dividing the number of residential customers by total number of customers on each transformer.

[c] PV installed capacity represents cumulative solar (nameplate) capacity of executed agreements on Net Energy Metering, feed-in-tariff and standard interconnection agreement programs.

Source: HECO

Table A.2: Volatility of Net Electricity Load by Time, Seasons, and Year.

Standard Deviation of Net Load (kW)		Mean	SD	Min	Max
Time of Day[a]	Day	385.9	249.4	3.6	1,800.5
	Night	210.6	162.0	3.1	1,789.0
Season[b]	Summer	261.8	215.5	3.1	1,746.9
	Winter	278.2	211.4	4.5	1,800.5
Year	2010	237.6	156.4	9.8	1,089.7
	2011	255.6	197.9	3.1	1,680.7
	2012	260.7	214.9	4.3	1,800.5
	2013	280.7	220.2	3.6	1,789.0
	2014	300.7	218.4	4.5	1,593.8

[a] Daytime is defined from 9:00am to 5:00pm whereas nighttime is from 5:15pm to 8:45am.

[b] Summer months are from May to October and winter months are from November to April.

Table A.3: Empirical Results.

	Dependent Variable: Log of SD of Net Load							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log of PV Penetration	0.033**	-0.053*	0.008	0.033**	-0.078***	-0.053*	0.008	-0.079***
	(0.017)	(0.028)	(0.017)	(0.017)	(0.029)	(0.017)	(0.029)	(0.029)
Temperature	0.052***	0.052***	0.051***	0.025	0.051***	0.026	0.023	0.023
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Humidity	-0.0001	0.0001	-0.0005	0.022***	-0.0004	0.022***	0.023***	0.023***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
Solar Irradiance	-0.145	-0.144	-0.503**	-0.288**	-0.502**	-0.286**	-0.662***	-0.661***
	(0.123)	(0.123)	(0.197)	(0.131)	(0.197)	(0.131)	(0.195)	(0.195)
Wind Speed	-0.018***	-0.018***	-0.018***	-0.018***	-0.018***	-0.018***	-0.018***	-0.018***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Day=1	0.827***	0.826***	0.818***	0.973***	0.817***	0.972***	0.973***	0.972***
	(0.102)	(0.102)	(0.095)	(0.107)	(0.095)	(0.107)	(0.101)	(0.100)
Summer=1	-0.334***	-0.334***	-0.333***	-0.285***	-0.333***	-0.284***	-0.281***	-0.280***
	(0.058)	(0.058)	(0.055)	(0.057)	(0.055)	(0.057)	(0.054)	(0.054)
%Residential*log of PV Penetration		0.099***			0.099***	0.099***		0.099***
		(0.028)			(0.028)	(0.028)		(0.028)
Solar Irradiance*log of PV Penetration			0.125**		0.125**		0.128**	0.128**
			(0.062)		(0.062)		(0.061)	(0.061)
Temperature*Humidity				-0.054***		-0.054***	-0.058***	-0.058***
				(0.012)		(0.012)	(0.012)	(0.012)
Constant	3.913***	3.926***	4.033***	2.447***	4.047***	2.461***	2.477***	2.490***
	(0.652)	(0.653)	(0.667)	(0.629)	(0.667)	(0.631)	(0.640)	(0.641)

Note: Numer of observations is 336,889. Standard errors are in parentheses and clustered at transformer level. *,**, and *** indeicate significance at the 90%, 95%, and 99% level, respectively.

Table A.4: Empirical Results – *Daytime Only*.

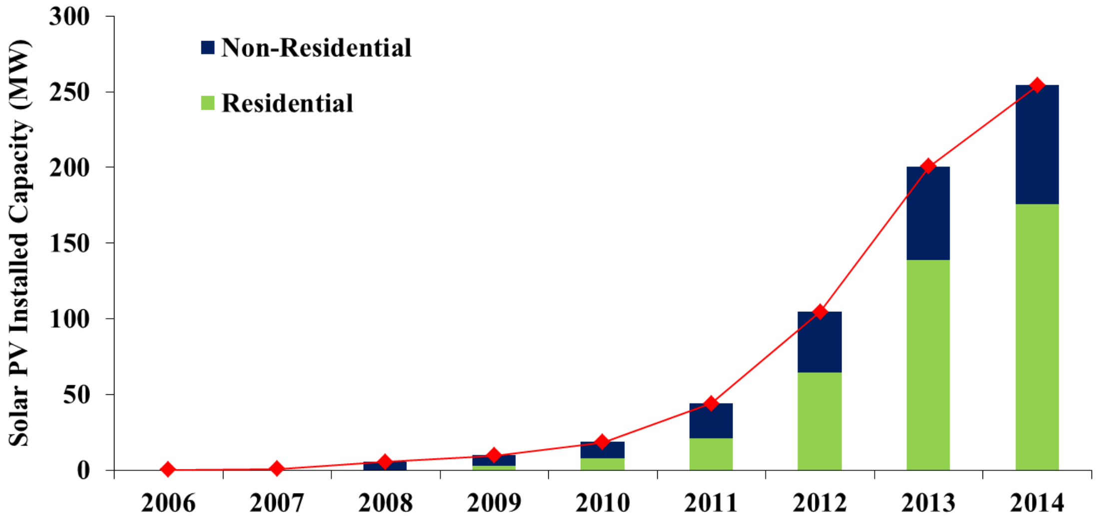
	Dependent Variable: Log of SD of Net Load							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
log of PV Penetration	0.095***	-0.095**	0.056**	0.095***	-0.136***	-0.095**	0.056**	-0.014***
	(0.028)	(0.039)	(0.024)	(0.028)	(0.037)	(0.039)	(0.024)	(0.037)
Temperature	0.022**	0.022**	0.021**	-0.017	0.022**	-0.017	-0.018	-0.018
	(0.010)	(0.009)	(0.009)	(0.011)	(0.009)	(0.011)	(0.011)	(0.011)
Humidity	-0.001	-0.001	-0.001	0.016***	-0.001	0.016***	0.016***	0.017***
	(0.001)	(0.001)	(0.001)	(0.004)	(0.001)	(0.004)	(0.004)	(0.004)
Solar Irradiance	-0.013	-0.004	-0.216**	-0.017	-0.213**	-0.008	-0.223**	-0.220**
	(0.086)	(0.085)	(0.106)	(0.083)	(0.106)	(0.083)	(0.103)	(0.103)
Wind Speed	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Summer=1	-0.175***	-0.172***	-0.177***	-0.098**	-0.174***	-0.095**	-0.098**	-0.094**
	(0.048)	(0.047)	(0.048)	(0.043)	(0.047)	(0.042)	(0.042)	(0.041)
%Residential*log of PV Penetration		0.219***			0.220***	0.219***		0.221***
		(0.035)			(0.035)	(0.035)		(0.035)
Solar Irradiance*log of PV Penetration			0.076***		0.078***		0.077***	0.079***
			(0.024)		(0.024)		(0.024)	(0.024)
Temperature*Humidity				-0.039***		-0.039***	-0.041***	-0.041***
				(0.011)		(0.011)	(0.011)	(0.012)
Constant	5.160***	5.184***	5.261***	4.524***	5.287***	4.548***	4.609***	4.636***
	(0.233)	(0.233)	(0.227)	(0.299)	(0.227)	(0.301)	(0.302)	(0.305)

Note: Daytime is from 9:am to 5:00pm. Numer of observations is 115,826. Standard errors are in parentheses and clustered at transformer level. *,**, and *** indeicate significance at the 90%, 95%, and 99% level, respectively.

Appendix B

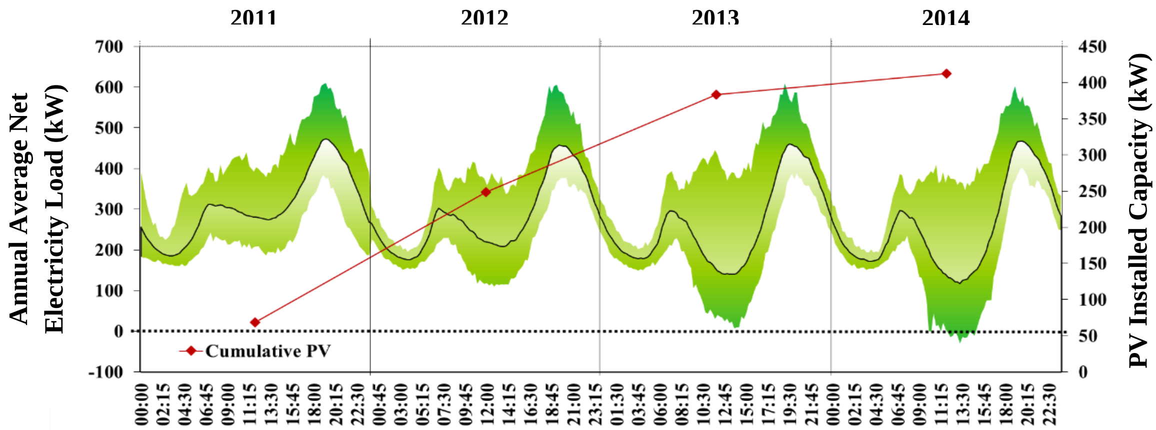
Figures for Chapter 1

Figure B.1: Annual Solar Installed Capacity by Customer Segment.



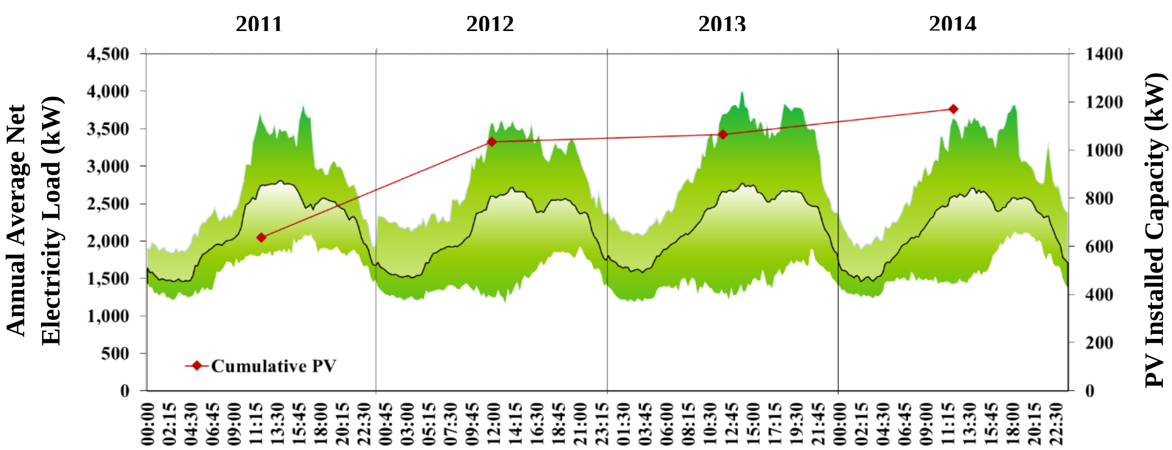
Notes: PV installed capacity shown in this figure consist of those distributed generation systems with executed agreements placed on or before December 2014. Residential and commercial customers are classified based on their rate schedules. Total annual PV capacity installed had increased every year since 2006. The rapid growth of solar installation has slowed down after 2012 when HECO implemented a 75% limit on level of solar penetration. Following this threshold limit, the growth rate of installed PV capacity fell to 57% from 2012 to 2013. A significant negative growth rate in PV installations from 2013 to 2014 due to a new threshold limit implemented in 2013 is observed in this graph.
Source: HECO.

Figure B.2: Variations in Net Electricity Load – *Residential*.



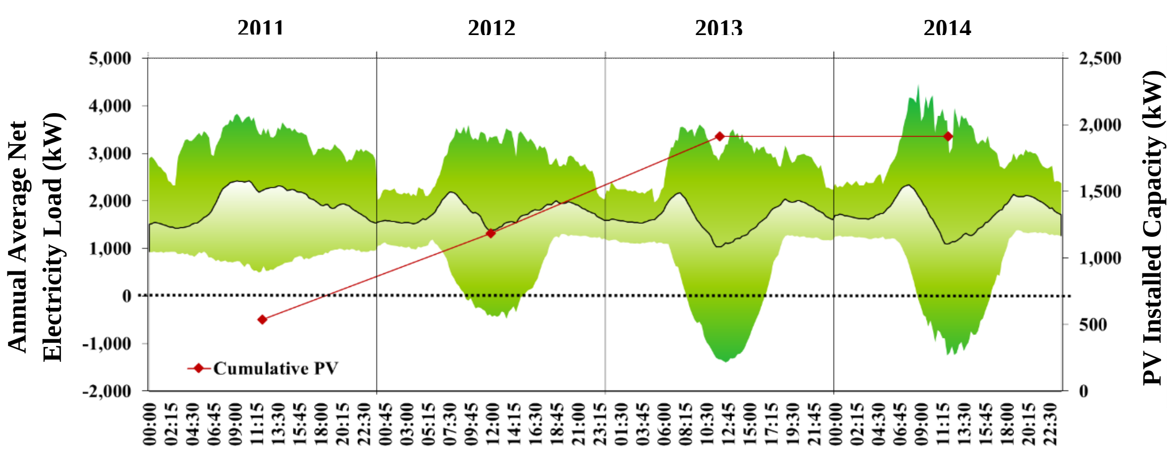
Source: HECO.

Figure B.3: Variations in Net Electricity Load – *Commercial*.



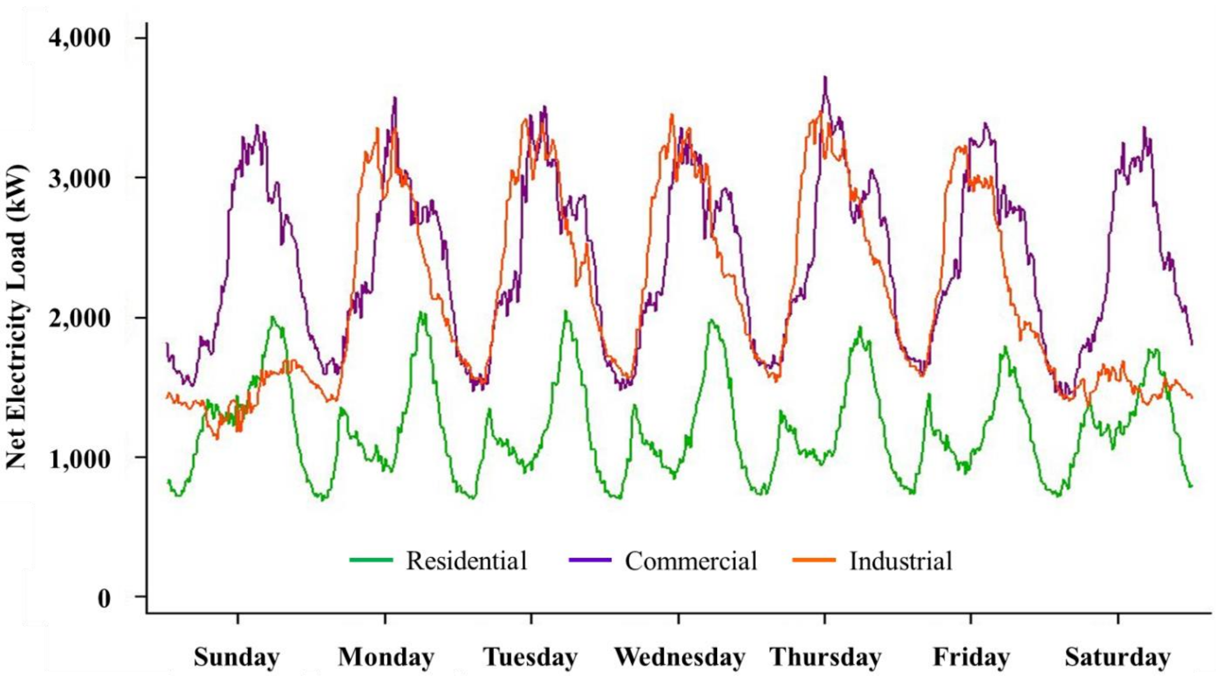
Source: HECO.

Figure B.4: Variations in Net Electricity Load – *Industrial*.



Source: HECO.

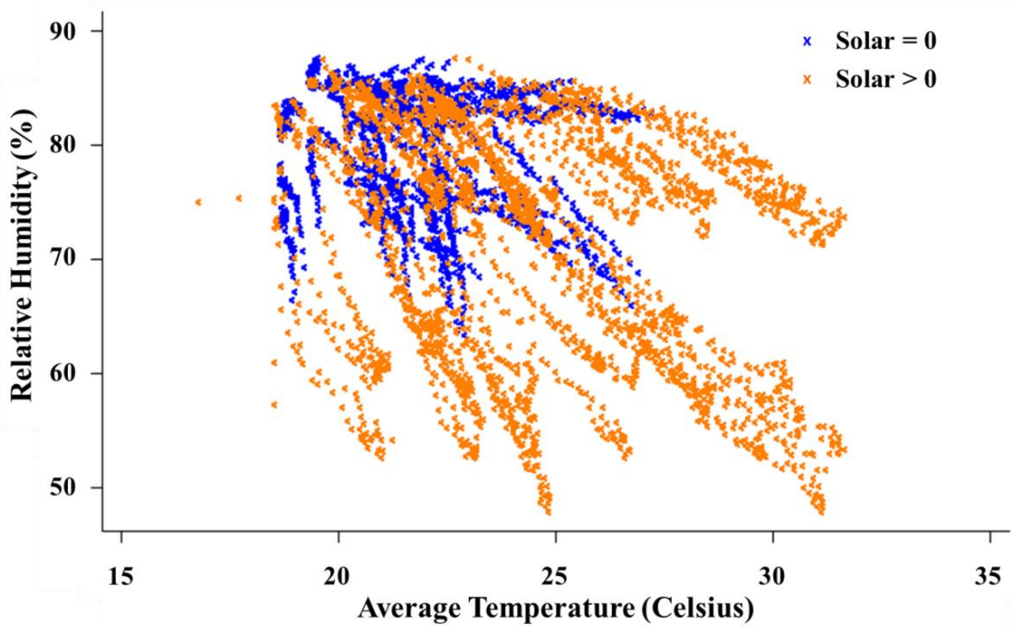
Figure B.5: 7-Day Net Load Profiles – *Residential, Commercial, Industrial Areas*.



Note: Data used in this figure covers a one-week period from 8/28/2011 to 9/3/2011.

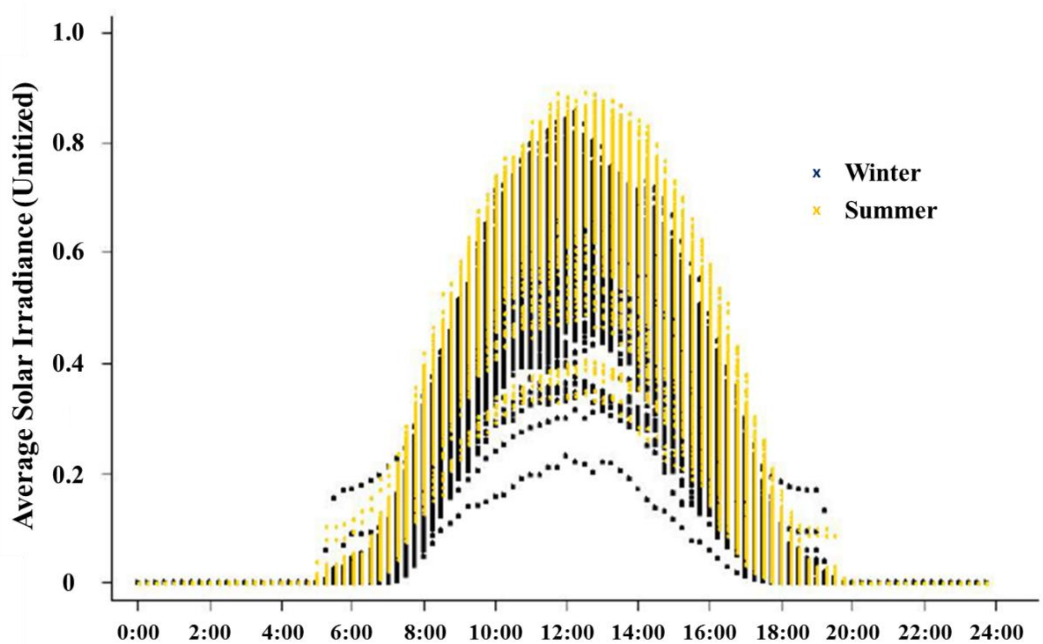
Source: HECO.

Figure B.6: Relationship between Temperature and Humidity – *Sun & No Sun*.



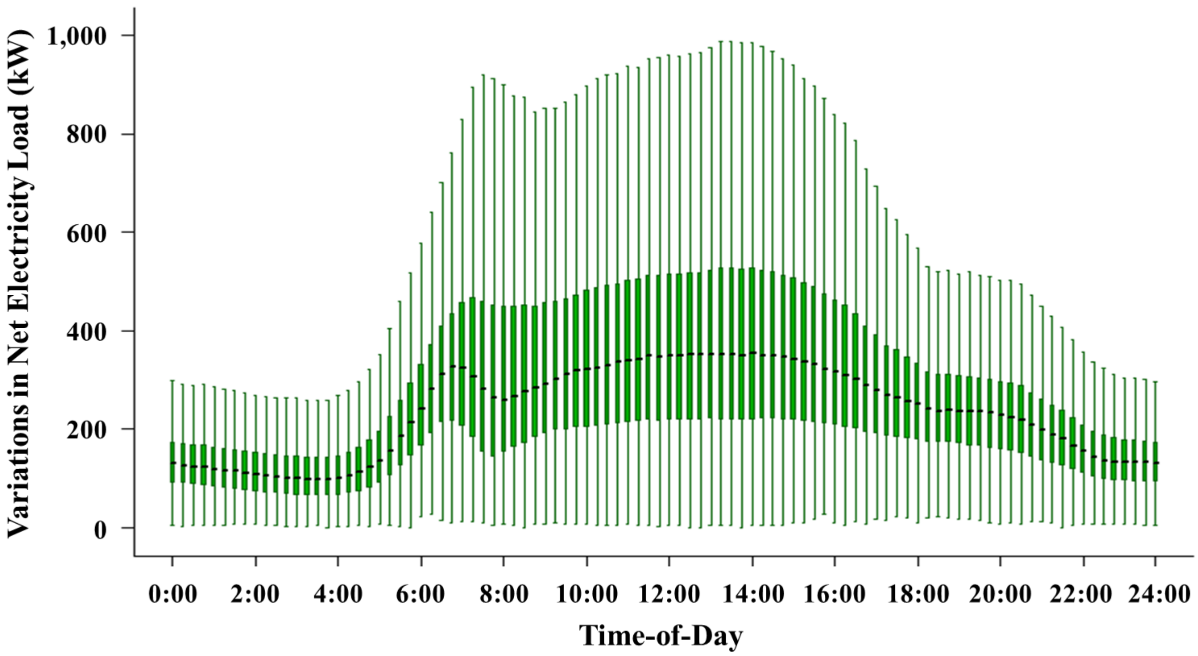
Source: HECO.

Figure B.7: Average Solar Irradiance by Time-of-Day – *Winter & Summer*.



Source: HECO.

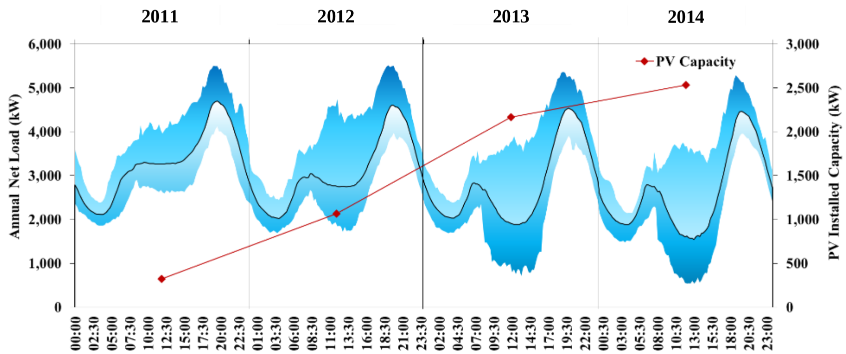
Figure B.8: Volatility of Net Electricity Load.



Note: Standard deviation of net electricity load in each 15-minute interval is used to represent variations in net electricity load. Outliers are excluded.

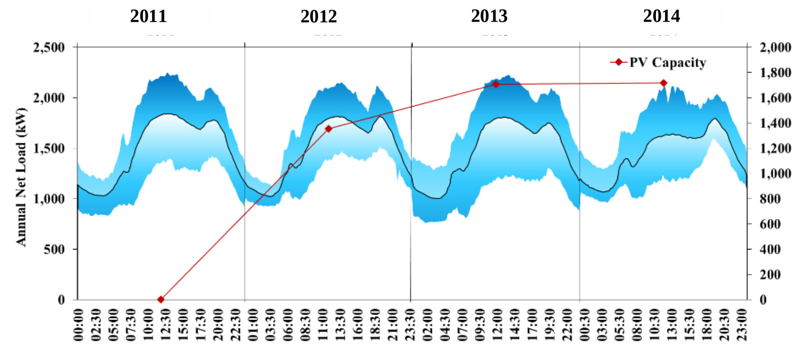
Source: HECO.

Figure B.9: Net Electricity Load of 4 Sample Transformers.



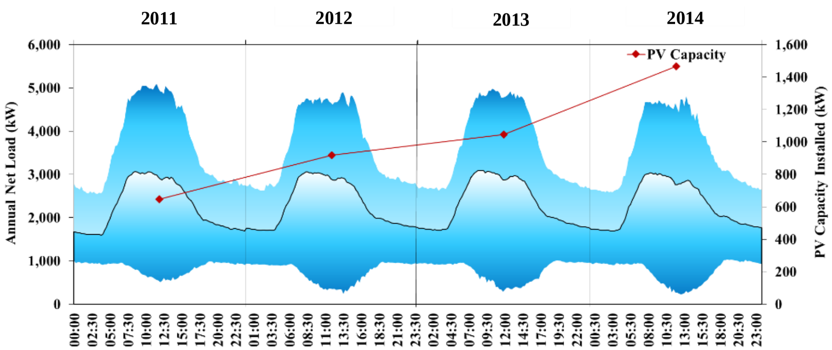
Source: HECO.

(a) Residential



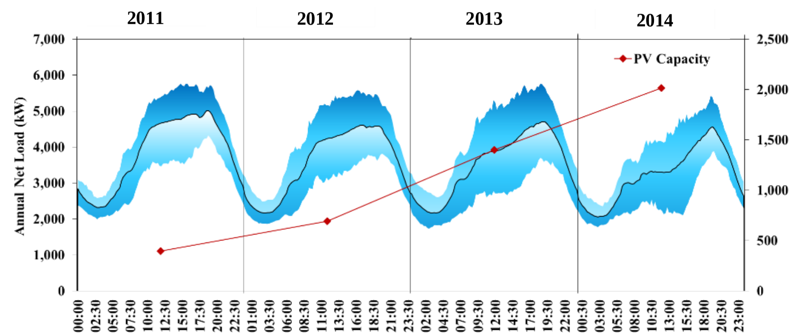
Source: HECO.

(b) Commercial



Source: HECO.

(c) Industrial



Source: HECO.

(d) Mix

Appendix C

Tables for Chapter 2

Table C.1: Summary Statistics & Difference in Means.

Variables	No PV Mean	No PV *SD*	PV Mean	PV *SD*	Difference in Means	p-value
Baseline Consumption (kWh)[a]	971.37	*699.97*	1,044.16	*616.82*	-72.79	0.0005
Maximum Solar Irradiance (W/m^2)[b]	205.32	*11.94*	205.83	*11.78*	-0.51	0.1836
Housing Characteristics						
Home Value ($/square foot)[c]	504.45	*196.03*	448.90	*167.82*	55.55	0.0000
Age of Homes (years)[d]	45.21	*15.88*	42.28	*16.23*	2.93	0.0000
Home Size (sqft)	1,913.19	*923.28*	2,225.20	*985.54*	-312.01	0.0000
Home Energy Intensity (kWh/Sqft)[e]	0.55	*0.33*	0.50	*0.26*	0.04	0.0001
Demographics						
Education (% College Degree or Higher)	38.52	*17.46*	39.29	*17.05*	-77%	0.1654
Family Size	3.27	*0.75*	3.25	*0.74*	0.02	0.3900
% Owner-Occupied Housing Units	73.65	*17.50*	73.83	*16.88*	-18%	0.7449
Median Household Income ($)	93,112.52	*27,213.31*	94,871.39	*26,782.92*	-1,758.87	0.0434
Median Age	43.43	*7.48*	43.05	*7.51*	0.37	0.1219

[a] We use monthly usage from 2000 to 2005 (excluding post-solar observations) to calculate baseline consumption.

[b] Maximum solar irradiance is the maximum value of monthly solar irradiance available at a household's premise, including the period spanning from 2003 to 2015.

[c] Property value per square foot is calculated by dividing a household's property value by home size.

[d] Age of home is calculated by subtracting 2016 by a home's year built.

[e] Monthly usage per sqft is calculated by dividing a household's "baseline" consumption by a home size

Table C.2: Marginal Effects for the Logit Model.

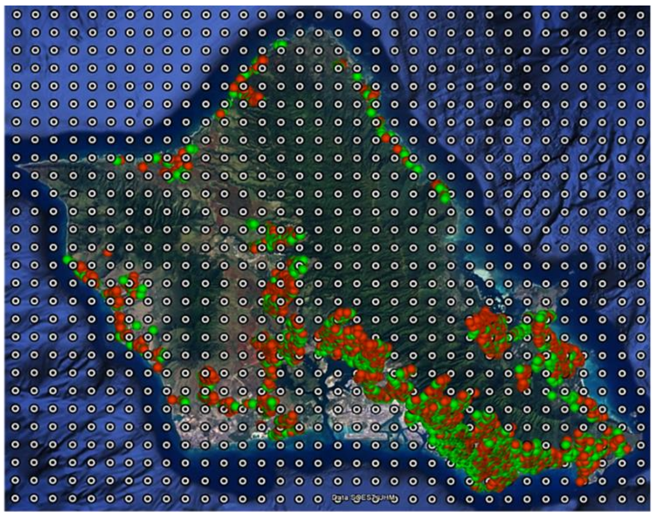
	Dependent Variable: Adopt Solar = 1 and 0 Otherwise			
	(1)	(2)	(3)	(4)
Baseline Consumption (kWh)	-1.02E-05	-9.56E-06	2.61E-05**	2.25E-05*
	(1.29E-05)	(1.29E-05)	(1.11E-05)	(1.28E-05)
Maximum Solar Irradiance (W/m2)	7.22E-04	7.10E-04	7.72E-04	7.53E-04
	(6.01E-04)	(6.02E-04)	(6.04E-04)	(6.02E-04)
Home Value ($/square foot)	-2.51E-04***	-2.61E-04***	-3.74E-04***	
	(5.02E-05)	(5.00E-05)	(4.55E-05)	
Age of Home	-1.08E-03**		-1.47E-03***	-1.28E-03***
	(4.68E-04)		(4.62E-04)	(4.68E-04)
Home Size (sqft)	5.74E-05***	6.04E-05***		8.29E-05***
	(1.08E-05)	(1.07E-05)		(9.72E-06)
Education (% College Degree or Higher)	0.011	-0.019	0.225***	-0.107
	(0.081)	(0.080)	(0.059)	(0.078)
Family Size	-0.030**	-0.037**	-0.012	-0.030**
	(0.015)	(0.015)	(0.013)	(0.015)
Homeownership (% Owner-Occupied Housing Units)	-0.049	-0.024	-0.055	-0.010
	(0.059)	(0.059)	(0.054)	(0.059)
Median Household Income ($)	6.89E-07	8.00E-07*		5.85E-07
	(4.44E-07)	(4.42E-07)		(4.46E-07)
Median Age	-0.003**	-0.004***	-0.002	-0.004***
	(1.35E-03)	(1.33E-03)	(1.33E-03)	(1.33E-03)
Having Solar Water Heater = 1	0.361***	0.362***	0.363***	0.366***
	(0.014)	(0.014)	(1.36E-02)	(1.34E-02)

Notes: This table shows the marginal effects of the logistic regression The dependent variable is a binary variable equals 1 if a household installed solar PV and 0 otherwise. The total number of households is 4,047, where 1,557 are non-PV and 2,490 are PV households. Standard errors are shown in parentheses. *,**, and *** indicates significance at the 90%, 95%, and 99% level, respectively.

Appendix D

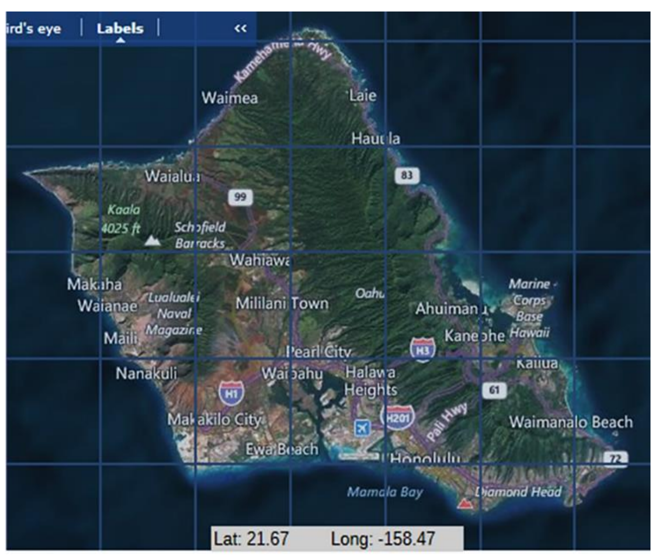
Figures for Chapter 2

Figure D.1: HECO/AWS Virtual Gridded Data Map – *Oahu*.



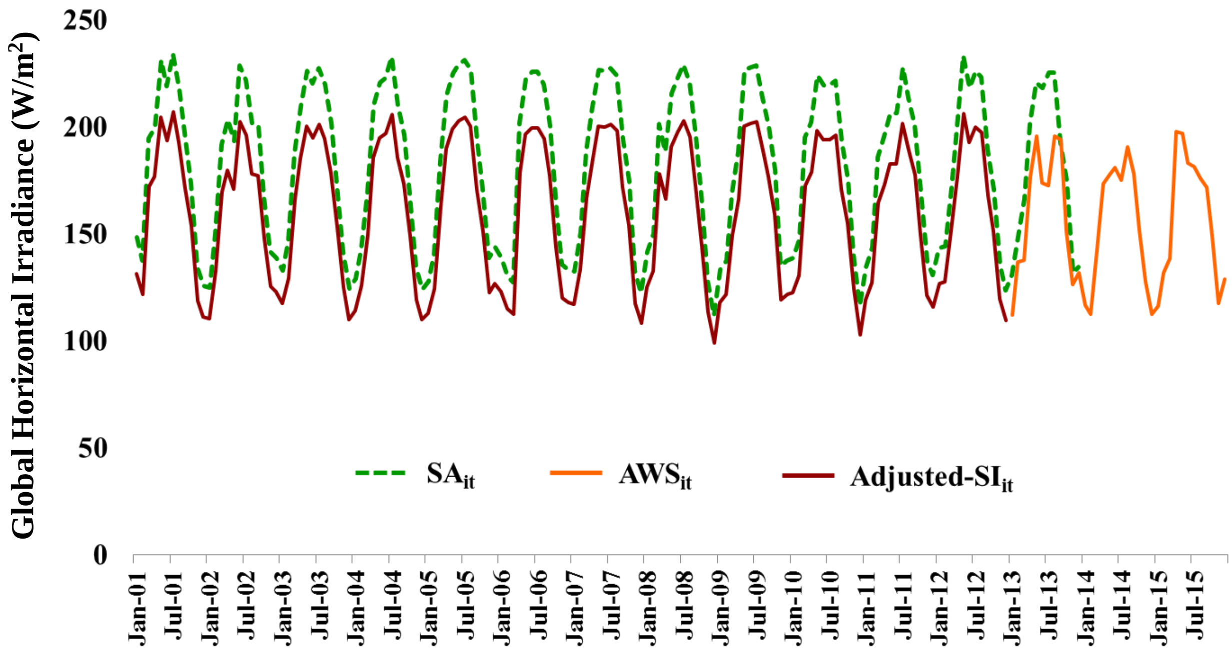
Note: Orange and green circles on the map represent locations of PV and non-PV households in the sample, respectively. Gridded points are 1 kilometer apart from one another.
Source: HECO & AWS Truepower

Figure D.2: SolarAnywhere Data Map – *Oahu*.



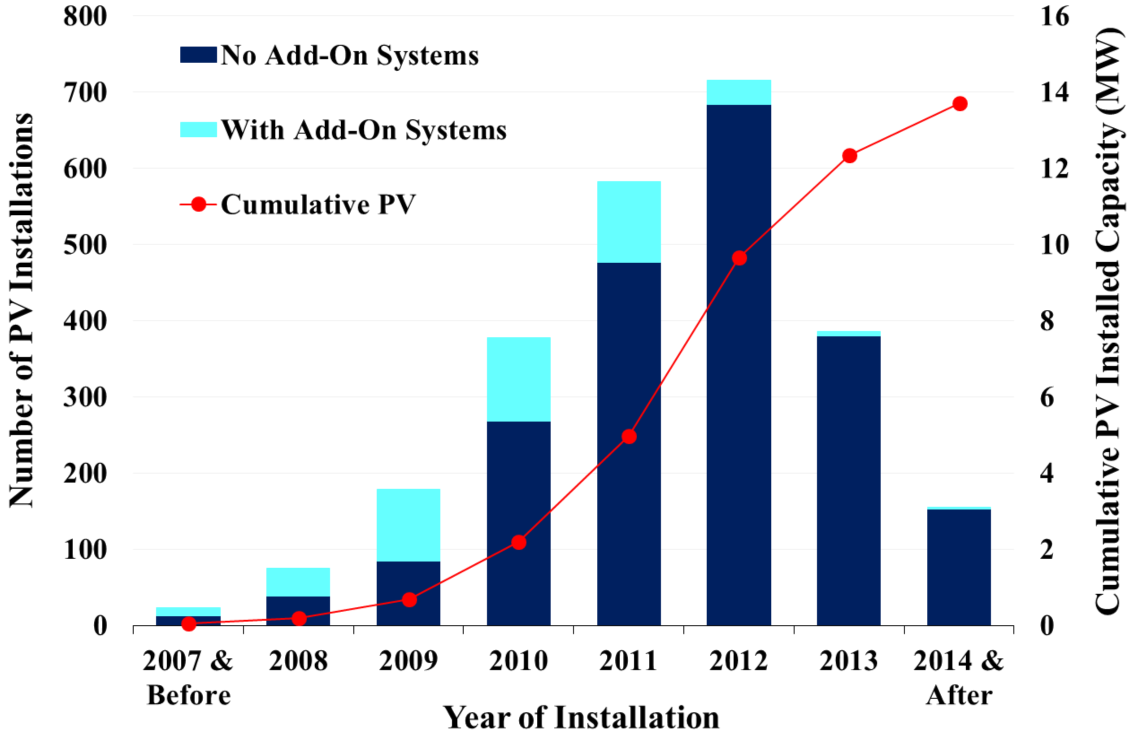
Note: Each tile is 10x10 kilometer.
Source: SolarAnywhere by Clean Power Research

Figure D.3: Estimated Monthly Solar Irradiance – ***A Sample Grid-Tile Data Point*.**



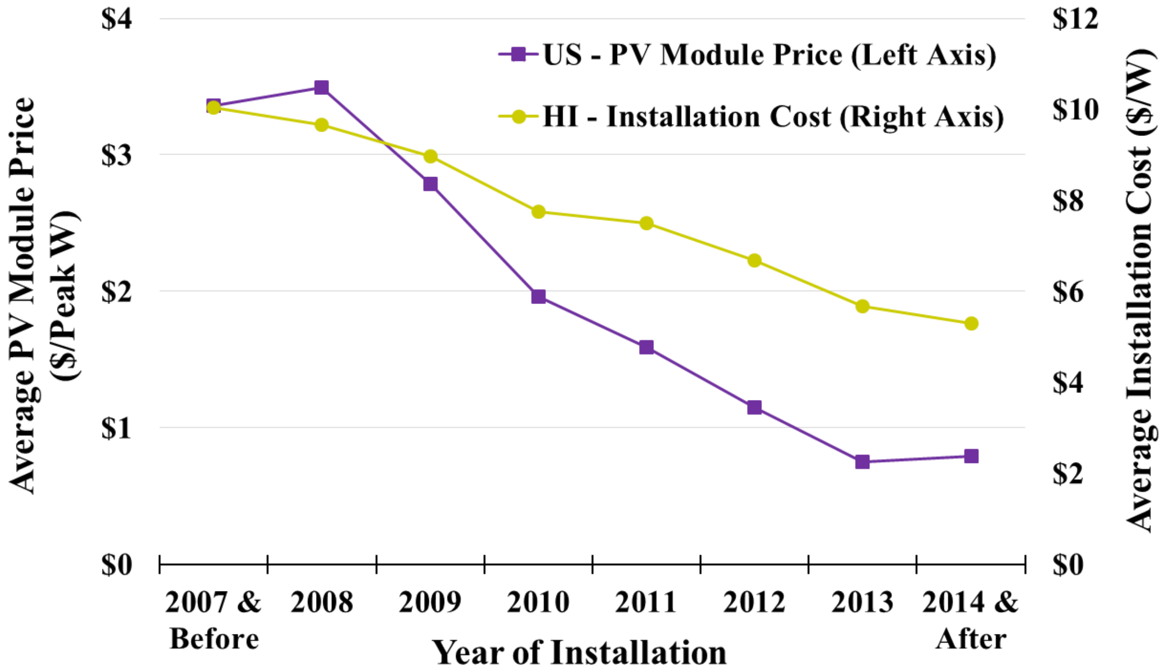
Source: HECO/AWS & SolarAnywhere

Figure D.4: Annual & Cumulative PV Installations (Samples).



Note: The figure shows the number of PV installations and cumulative PV capacity installed of customers in the study sample.
Source: HECO

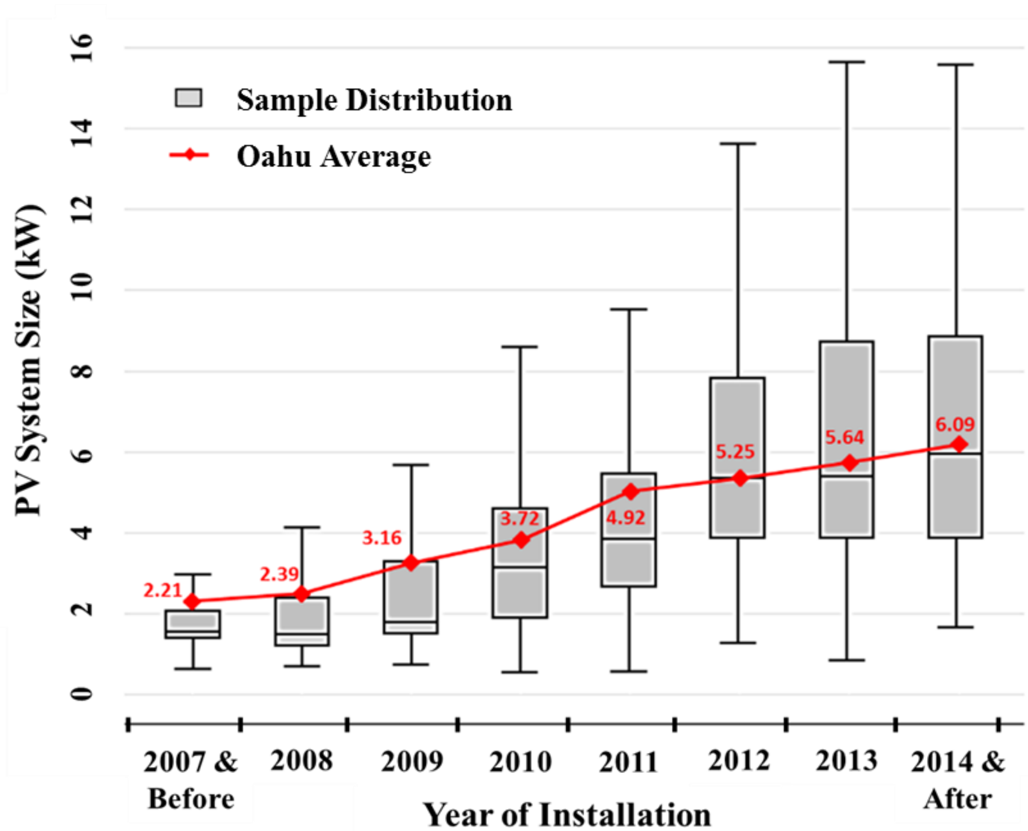
Figure D.5: Average PV Module Price & Total PV Installation Cost.



Note: The total PV installation costs obtained from DPP are calculated from the construction value submitted by applicants in their building permit application. These values, however, may include several components which are not necessarily related to the PV installations. To our knowledge, there is not enough data available to separate out such components. Therefore, in this study, these values are used as the best available proxy for the "actual" cost of PV installations.

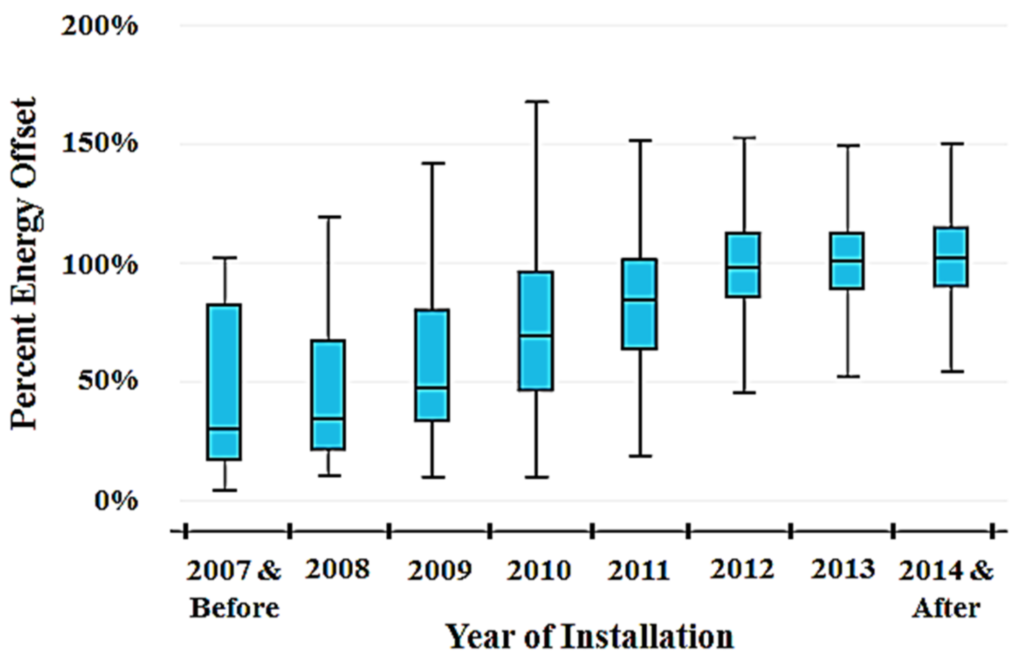
Source: HECO and U.S. EIA

Figure D.6: PV System Size Distribution.[35]



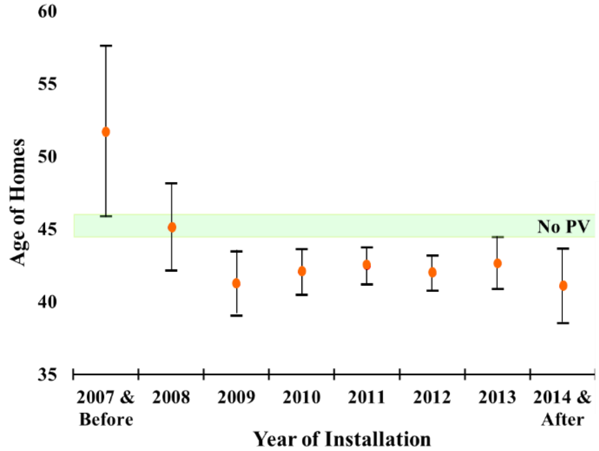
[35] Figure D.6 additionally shows how population average of PV system size (average system size of all residential NEM customers in Hawaii) on each year mostly lies within 50% of the sample's PV system size distribution.

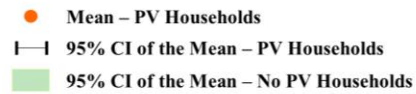
Figure D.7: Percent Energy Offset from PV.



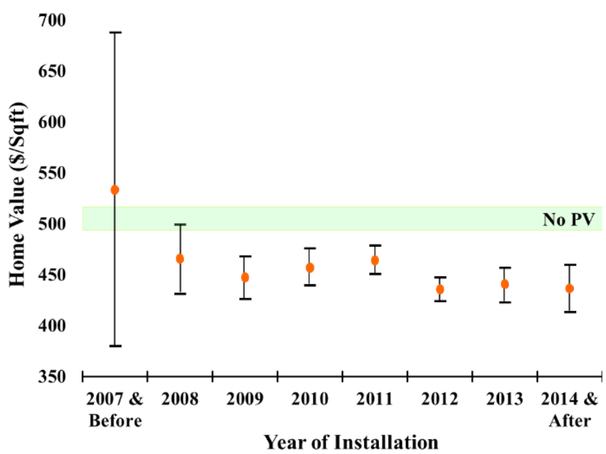
Note: Percent energy offset by PV systems is calculated by dividing estimated PV energy output by gross electricity consumption of the 12 months before PV installation. **Source:** HECO

Figure D.8: Housing Characteristics.

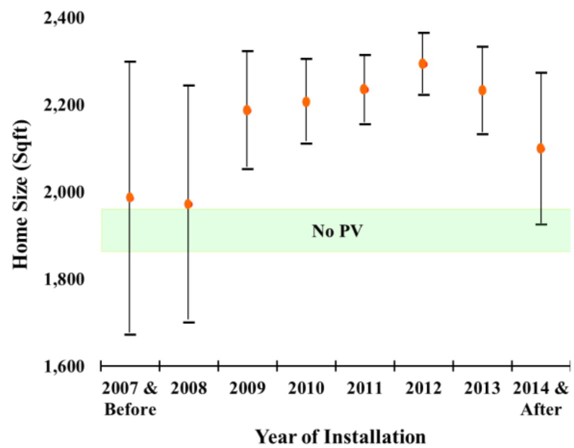




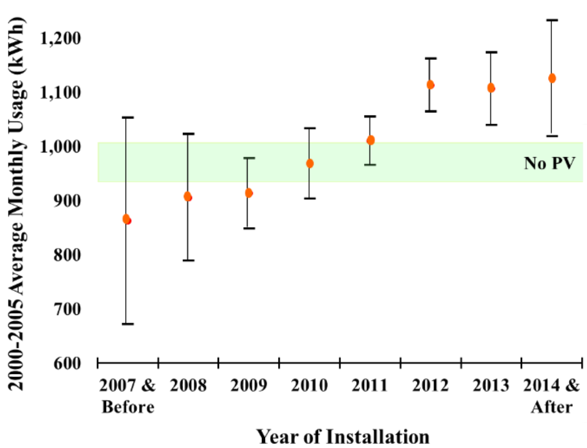
(a) Age of Home.



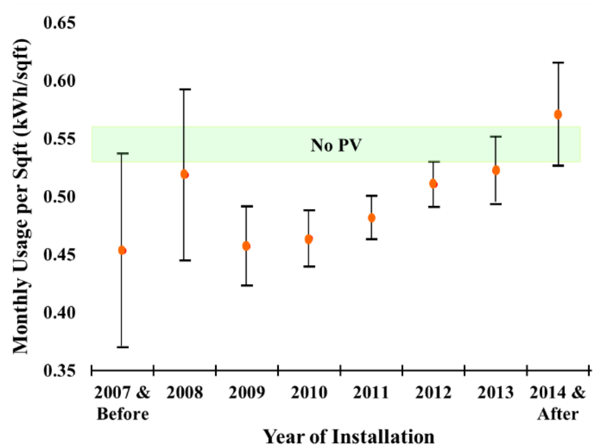
(b) Home Value.



(c) Home Size.

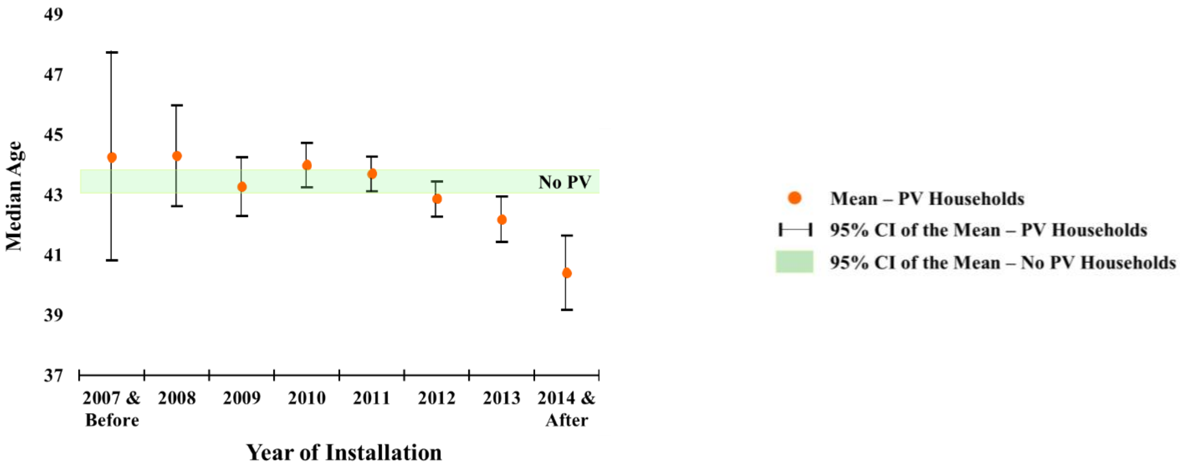


(d) Baseline Consumption.

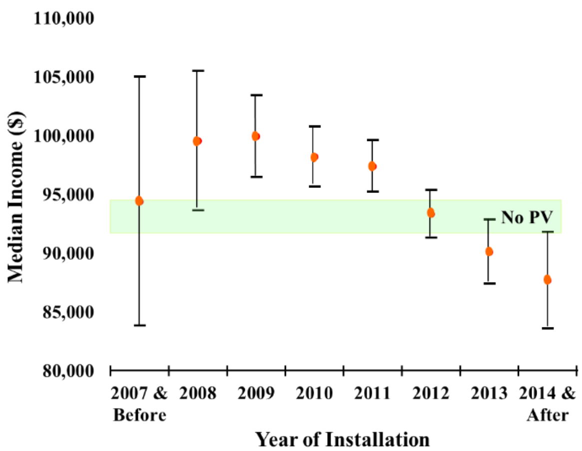


(e) Energy Intensity.

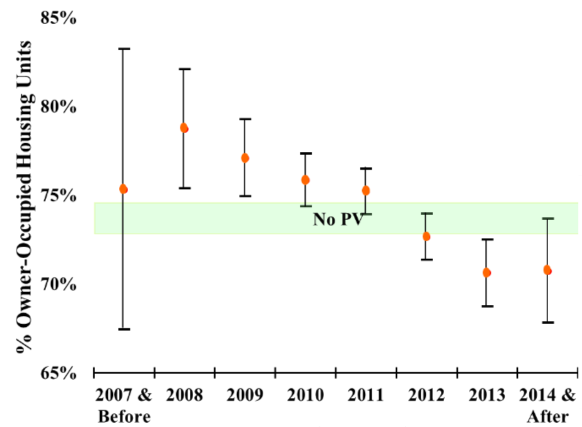
Figure D.9: Households' Demographics.



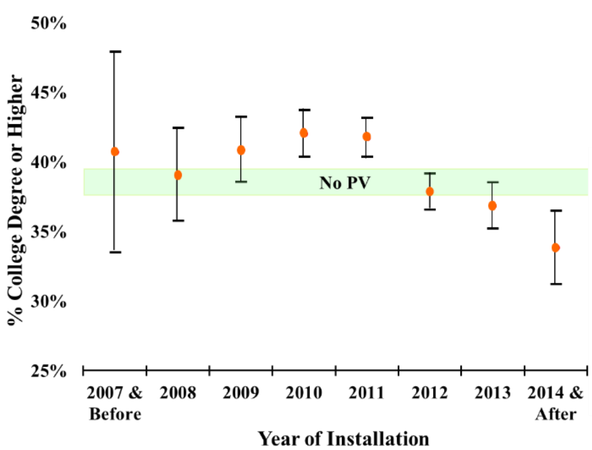
(a) Median Age.



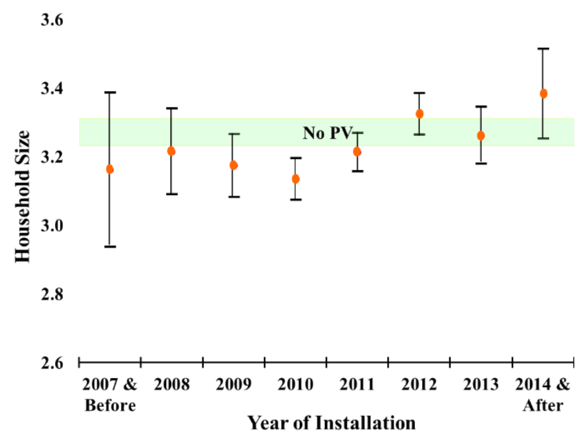
(b) Median Income.



(c) Homeownership.



(d) Education.



(e) Family Size.

Appendix E

Random Sampling Methodology

The following section summarizes the random sampling procedures used in this dissertation. The purpose of this was to develop characteristics and estimates of electricity consumption of residential customers, both with and without rooftop PV, using samples randomly selected within each category. Let $Cust_o$ be the total number of residential customers on Oahu and

$$\mathrm{Cust_o = PV_o + NoPV_o}$$

where PV_o and $NoPV_o$ are the number of residential customers on Oahu with and without solar PV installation, respectively. Let the index c represent circuit (strata) c on the Oahu electrical grid, where $c = 1, 2, 3, \ldots, b$ and b is the total number of circuits consisting of at least one residential customer (for Oahu $b = 323$). Let $Cust_c$ be the number of residential customers on circuit c and

$$\mathrm{Cust_c = PV_c + NoPV_c}$$

$$\mathrm{PV_o} = \sum_{c=1}^{b} \mathrm{PVc} \quad \text{and} \quad \mathrm{NoPV_o} = \sum_{c=1}^{b} \mathrm{NoPVc}$$

where PV_C and $NoPV_c$ are the number of residential customers on circuit c with and without solar PV installation, respectively.

For the purposes of this dissertation, assume the initial sample consisted of 2,500 non-PV residential customers and 3,000 PV residential customers. In order to ensure that a representative number of customers was selected from each circuit, the number to select from each was calculated as follows:

$$N_c^{PV} = \frac{PVc}{PVo} *3{,}000 \qquad \text{and} \qquad N_c^{NoPV} = \frac{NoPVc}{NoPVo} *2{,}500$$

where N_c^{PV} and N_c^{NoPV} are the number of residential samples with and without solar PV installation on circuit c, respectively.

Appendix F

Tables for Chapter 3

Table F.1: Summary of Electricity Demand Studies.

Author(s)	Country	Study Period	Data	Methodology[a]	Price Elasticity[b]
Halvorsen (1975)	USA	1961-1969	Annual	Static,Dynamic Models	-1.52
Filippini (1999)	Switzerland	1987-1990	Annual	OLS,LSDV,ECM	-0.30
Bose and Shukla (1999)	India	1985-1993	Annual	Static,Dynamic Models	-0.65
Bjørner et al. (2001)	Denmark	1983-1996	Annual	FE	-0.40
Al-Faris (2002)	GCC[c]	1970-1997	Annual	Cointegration,ECM	-0.18 to -0.04
Filippini and Pachauri (2004)	India	1993-1994	Monthly	OLS	-0.51 to -0.29
Kamerschen and Porter (2004)	USA	1973-1998	Annual	PAM,SE	-0.94 to -0.85
Holtedahl and Joutz (2004)	Taiwan	1955-1995	Annual	Cointegration,ECM	-0.16
Narayan and Smyth (2005)	Australia	1969-2000	Annual	ARDL	-0.26
Reiss and White (2005)	California	1993-1997	Annual	GMM,OLS	-0.39 to -0.28
Bernstein et al. (2006)	USA	1977-2004	Annual	PAM	-0.31 to -0.04
Halicioglu (2007)	Turkey	1968-2005	Annual	Cointegration,ARDL	-0.46 to -0.33
Atakhanova and Howie (2007)	Kazakhstan	1994-2003	Annual	Panel GMM	-0.22 to -1.10
Erdogdu (2007)	Turkey	1984-2004	Quarterly	PAM,Cointegration	-0.04 to -0.01
Dergiades and Tsoulfidis (2008)	USA	1965-2006	Annual	ARDL	-0.39
Ziramba (2008)	South Africa	1978-2005	Annual	Cointegration,ARDL	-0.02
Paul et al. (2009)	USA	1990-2006	Monthly	PAM	-0.21 to -0.05
Sa'ad (2009)	South Korea	1973-2007	Annual	STSM,Kalman Filter	-0.14
Amusa et al. (2009)	South Africa	1960-2007	Annual	Cointegration,ARDL	-0.04
Athukorala and Wilson (2010)	Sri Lanka	1960-2007	Annual	Cointegration,ECM	-0.16
Alberini et al. (2011)	USA	1997-2007	Annual	PAM	-0.89 to -0.74
Fan and Hyndman (2011)	Australia	1997-2008	Half-Hourly	Semi-PAA	-0.43 to -0.36
Alberini and Filippini (2011)	USA	1995-2007	Annual	PAM	-0.15 to -0.08
Lee and Chiu (2011)	OECD[d]	1978-2004	Annual	PSTR	-0.23
Dilaver and Hunt (2011)	Turkey	1960-2008	Annual	STSM	-0.38
Labandeira et al. (2012)	Spain	2005-2007	Monthly	GLS	-0.25 to -0.03
Zhou and Teng (2013)	China	2007-2009	Annual	OLS	-0.50 to -0.35
Blázquez et al. (2013)	Spain	2000-2008	Annual	PAM	-0.11
Okajima and Okajima (2013)	Japan	1990-2007	Annual	PAM	-0.39
Lim et al. (2014)	South Korea	1970-2011	Annual	Cointegration,ECM	-0.42
Arisoy and Ozturk (2014)	Turkey	1960-2008	Annual	TVP,Kalman Filter	-0.02

[a] ARDL = Autoregressive distributive lag, ECM = Error correction model, FE = Fixed-effects estimator, GLS = Generalized least squares, GMM = Generalized method of moments, LSDV = Least square dummy variable, OLS = Ordinary least squares, PAM = Partial adjustment model, PSTR = Panel smooth transition regression, SE = Simultaneous equation, Semi-PAA = Semi-parametric additive model, STSM = Structural time series model, and TVP= Time varying parameter approach

[b] This table reports short-run residential price elasticities of electricity demand only.

[c] GCC stands for Gulf Cooperation Council which includes Saudi Arabia, United Arab Emirates, Kuwait, Oman, Bahrain, and Qatar.

[d] 24 OECD countries include Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, South Korea, Luxembourg, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, UK, and USA.

Table F.2: Summary Statistics of Monthly Electricity Usage – *PV & No PV*

		Monthly Usage (kWh)				
		Mean	SD	Min	Median	Max
Baseline Period: Jan 2000 to Dec 2009						
	No PV	957.02	726.20	96	783	12,640
Pre-Solar	PV	1,041.91	653.87	72	884	9,920
Overall Period - Jan 2000 to May 2016						
	No PV	907.13	697.23	93	736	12,640
Pre-Solar	PV	1,034.69	650.79	72	878	9,920
Post-Solar (Gross)	PV	906.33	598.95	80	755	8,689
Post-Solar (Net)	PV	192.41	402.17	-2,240	107	6,320

Notes: Net monthly usage is the difference between the amount of energy delivered from the grid to customers' homes and the excess energy generated from PV systems being sent back to the grid. Gross monthly usage is the sum of net monthly usage and the estimated PV energy output.

Table F.3: Summary Statistics of Other Variables.

	Prices, Weather & PV			
	Mean	SD	Min	Max
Real Electricity Price (cents/kWh)	25.44	6.26	16.28	37.58
Maximum Temperature (F)	87.26	2.83	82	93
Total Precipitation (inches)	1.36	2.13	0.01	16.92
Average Wind Speed (mph)	9.8	1.88	5	13
PV System Size (kW)[a]	5.05	3.33	0.28	35.90

[a] Initial PV sytem size (kW) - nameplate capacity

Table F.4: Summary Statistics of Monthly Electricity Usage – *By PV Sizing Group.*

		Monthly Usage (kWh)				
		Mean	SD	Min	Median	Max
Baseline Period: Jan 2000 to Dec 2009						
	No PV	957.02	726.20	96	783	12,640
Pre-Solar	**PV - Net Import**	1,166.04	756.75	103	974	9,920
	PV - Net Zero	979.73	599.20	72	834	8,640
	PV - Net Export	661.81	489.48	111	527	4,913
Overall Period - Jan 2000 to May 2016						
	No PV	907.13	697.23	93	736	12,640
PV - Net Import	**Pre-Solar**	1,174.19	757.41	103	983	9,920
	Post-Solar (Gross)	937.70	650.71	80	766	8,038
	Post-Solar (Net)	324.68	446.53	-1,911	216	6,320
PV - Net Zero	**Pre-Solar**	966.46	589.84	72	823	8,640
	Post-Solar (Gross)	900.93	606.59	93	741	8,689
	Post-Solar (Net)	46.75	295.51	-2,240	3	4,080
PV - Net Export	**Pre-Solar**	633.38	462.93	102	506	4,913
	Post-Solar (Gross)	704.53	478.69	101	573	3,016
	Post-Solar (Net)	-98.63	278.38	-1,684	-74	1,073

Notes: Net monthly usage is the difference between the amount of energy delivered from the grid to customers' homes and the excess energy generated from PV systems being sent back to the grid. Gross monthly usage is the sum of net monthly consumption and the estimated PV energy output.

Table F.5: Empirical Results for Electricity Demand Model (3.8) and (3.9).

	Dependent Variable: Log of Gross Electricity Consumption		
Period Considered	**(1) Baseline 2000-2009**	**(2) Overall 2000-2016**	**(3) Overall 2000-2016**
ln($Price_{t-1}$)	-0.117***	-0.099***	-0.099***
	(0.008)	(0.007)	(0.007)
ln($Price_{t-1}$)*PV	0.006	-0.043***	-0.004
	(0.011)	(0.013)	(0.013)
ln($Price_{t-1}$)*PV*PostPV		-0.111***	-0.067***
		(0.032)	(0.032)
ln(Temperature)	0.221***	0.244***	0.244***
	(0.027)	(0.023)	(0.023)
ln(Wind)	-0.020***	-0.028***	-0.028***
	(0.002)	(0.002)	(0.002)
ln(Precipitation)	-8.14E-04***	0.003***	0.003***
	(3.10E-04)	(2.46E-04)	(2.46E-04)
ln(Temperature)*PV	0.106***	0.126***	-0.186***
	(0.036)	(0.033)	(0.034)
ln(Wind)*PV	-0.003	-0.024***	0.014***
	(0.003)	(0.002)	(0.003)
ln(Precipitation)*PV	2.85E-04	0.005***	0.001
	(4.16E-04)	(3.59E-04)	(3.62E-04)
ln(Temperature)*PV*PostPV			1.325***
			(0.044)
ln(Wind)*PV*PostPV			0.015***
			(0.005)
ln(Precipitation)*PV*PostPV			0.008***
			(6.83E-04)

Notes: This table shows the results of the demand regression in equation (9) and (10), with fixed effect and control variables specified in the equation. The dependent variable is the log of gross electricity consumption. The sample period is from January 2000 to May 2016. The total number of households is 3,650, where 1,557 are non-PV and 2,093 are PV households. *PV* is a dummy variable equals 1 if a household had installed PV at some point in the study period. *PostPV* is an indicator equals 1 for the period after a household had installed solar PV. Standard errors in parentheses are clusteres at the household level to adjust for serial correlation. *,**, *** indicates significance at the 90%, 95%, and 99% level, respectively.

Table F.6: Empirical Results for Electricity Demand Model (3.10) and (3.11).

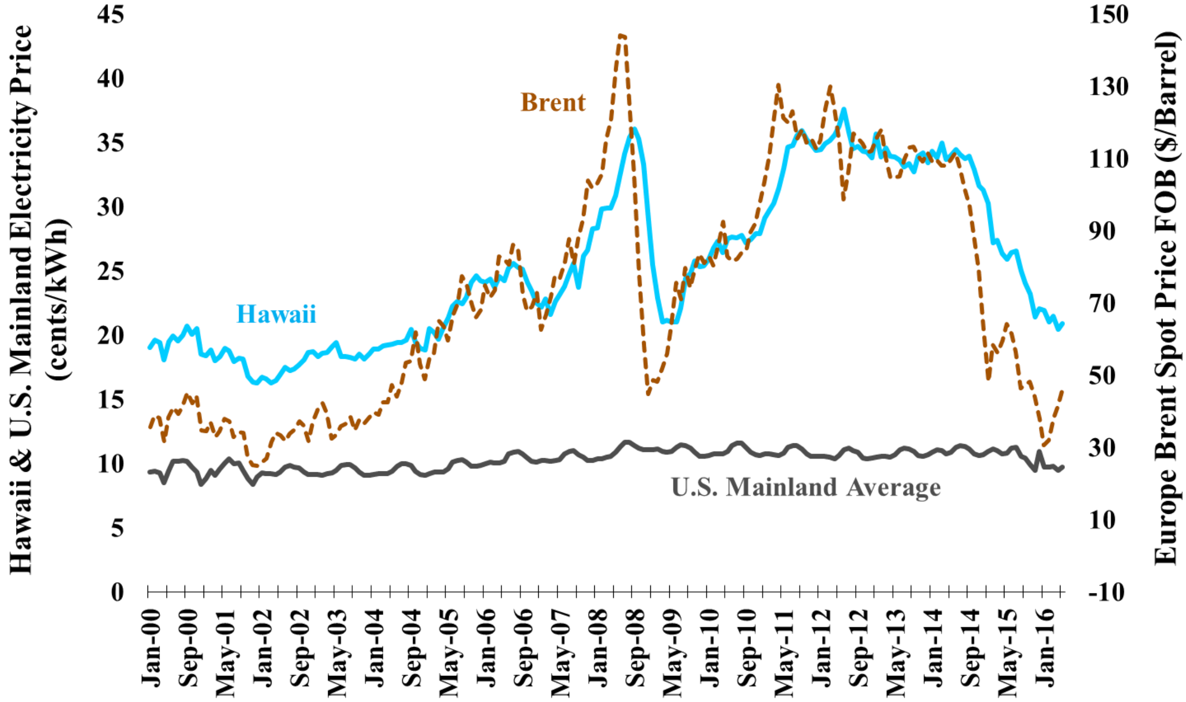
	Dependent Variable: Log of Gross Electricity Consumption										
Period Considered	(4) Baseline 2000-2009	(5) Overall 2000-2016	(6) Overall 2000-2016		(4) Baseline 2000-2009	(5) Overall 2000-2016	(6) Overall 2000-2016		(4) Baseline 2000-2009	(5) Overall 2000-2016	(6) Overall 2000-2016
ln(Price$_{t-1}$)	-0.141***	-0.122***	-0.119***	**ln(Temperature)**	0.183***	0.161***	0.177***				
	(0.009)	(0.007)	(0.007)		(0.029)	(0.026)	(0.026)				
ln(Price$_{t-1}$)*NI	0.111***	0.106***	0.124***	**ln(Temperature)*NI**	0.356***	0.554***	0.216***	**ln(Temperature)*NI*PostPV**			-0.466
	(0.020)	(0.019)	(0.019)		(0.066)	(0.065)	(0.065)				(0.420)
ln(Price$_{t-1}$)*NZ	0.013	-0.014	0.025*	**ln(Temperature)*NZ**	0.060	0.112***	-0.227***	**ln(Temperature)*NZ*PostPV**			-0.225
	(0.013)	(0.015)	(0.015)		(0.044)	(0.041)	(0.042)				(0.420)
ln(Price$_{t-1}$)*NE	-0.220***	-0.256***	-0.203***	**ln(Temperature)*NE**	-0.257	-0.256	-0.663***	**ln(Temperature)*NE*PostPV**			1.643***
	(0.085)	(0.069)	(0.073)		(0.225)	(0.229)	(0.221)				(0.414)
				ln(Wind)	-0.023***	-0.032***	-0.031***				
					(0.002)	(0.002)	(0.002)				
ln(Price$_{t-1}$)*NI*PostPV		-0.225***	-0.186***	**ln(Wind)*NI**	0.009**	-0.010**	-0.005	**ln(Wind)*NI*PostPV**			0.046
		(0.030)	(0.030)		(0.004)	(0.004)	(0.004)				(0.041)
ln(Price$_{t-1}$)*NZ*PostPV		-0.184***	-0.122***	**ln(Wind)*NZ**	0.001	-0.020***	-0.009***	**ln(Wind)*NZ*PostPV**			0.044
		(0.035)	(0.036)		(0.003)	(0.003)	(0.003)				(0.041)
ln(Price$_{t-1}$)*NE*PostPV		-0.122*	0.019	**ln(Wind)*NE**	-0.018	-0.052***	-0.024	**ln(Wind)*NE*PostPV**			-0.027
		(0.064)	(0.124)		(0.017)	(0.016)	(0.016)				(0.041)
				ln(Precipitation)	-0.001***	0.003***	0.003***				
					(3.38E-04)	(2.66E-04)	(2.66E-04)				
				ln(Precipitation)*NI	0.001	0.004***	2.82E-04	**ln(Precipitation)*NI*PostPV**			-0.013**
					(0.001)	(0.001)	(0.001)				(0.006)
				ln(Precipitation)*NZ	0.001*	0.006***	0.001*	**ln(Precipitation)*NZ*PostPV**			-0.011*
					(0.001)	(4.39E-04)	(4.54E-04)				(0.006)
				ln(Precipitation)*NE	-0.001	0.007**	-3.62E-04	**ln(Precipitation)*NE*PPostPV**			0.020***
					(0.003)	(0.003)	(0.003)				(0.005)

Notes: This table shows the results of the demand regression in equation (11) and (12), with fixed effect and control variables specified in the equation. The dependent variable is the log of gross electricity consumption. The sample period is from January 2000 to May 2016. The total number of households is 3,650, where 1,557 are non-PV and 2,093 are PV households. Of these PV households, 861 are Net Import, 1,188 are Net Zero, and 44 are Net Export households. *PV* is a dummy variable equals 1 if a household had installed PV at some point in the study period. *PostPV* is an indicator equals 1 for the period after a household had installed solar PV. Standard errors in parentheses are clusteres at the household level to adjust for serial correlation. *,**, and *** indicates significance at the 90%, 95%, and 99% level, respectively.

Appendix G

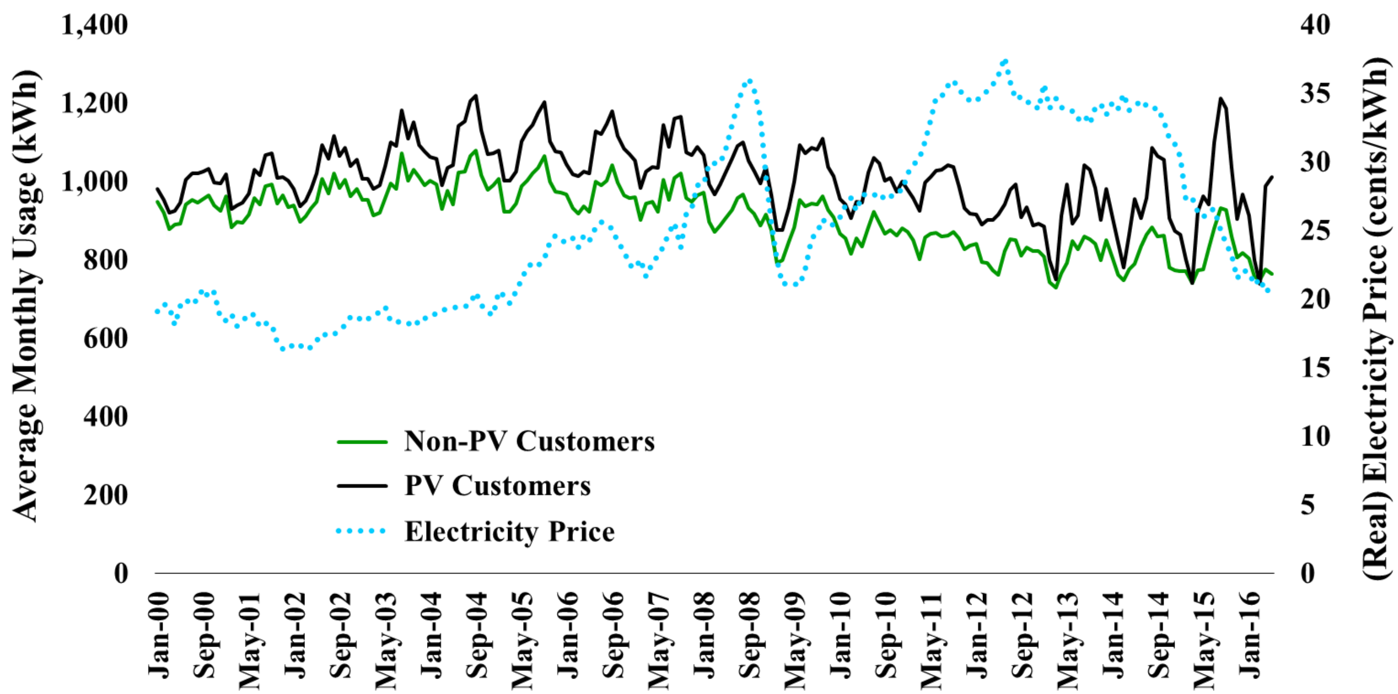
Figures for Chapter 3

Figure G.1: Electricity Prices & Brent Crude Oil Price.



Note: Both prices are adjusted for inflation, normalizing to 2015 dollar values.
Source: DBEDT & EIA

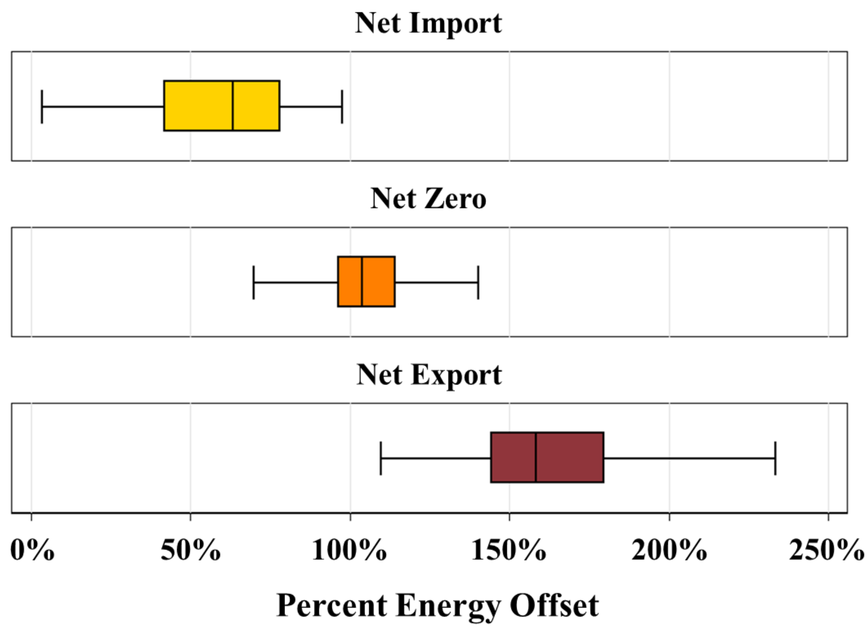
Figure G.2: Average Monthly Electricity Usage.



Note: This figure shows average monthly electricity consumption of households in the study sample. The black line represents gross energy consumption of single-family PV households having installed one PV system only. The number of customers having PV installed differs in each time period.

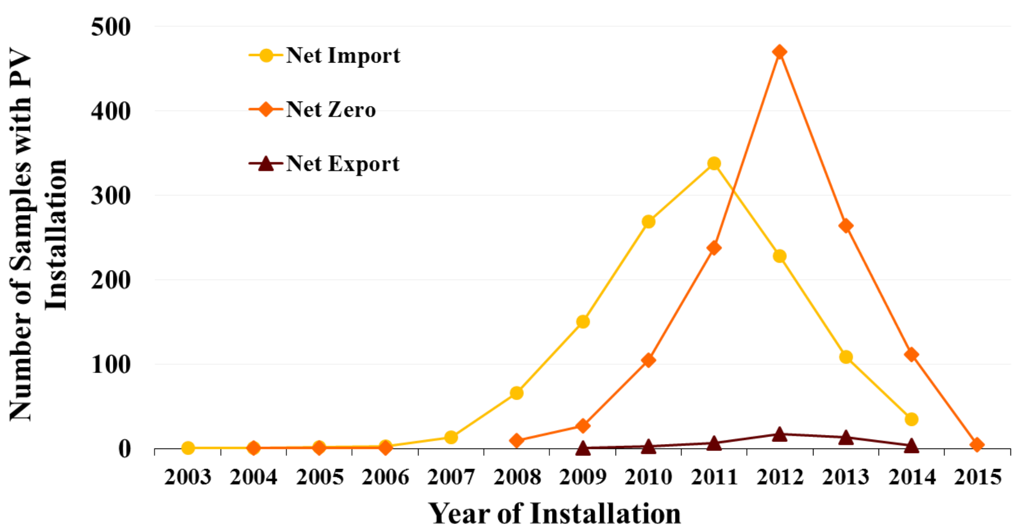
Source: HECO, EIA and DBEDT

Figure G.3: Percent Energy Offset by PV – *By PV Sizing Group*.



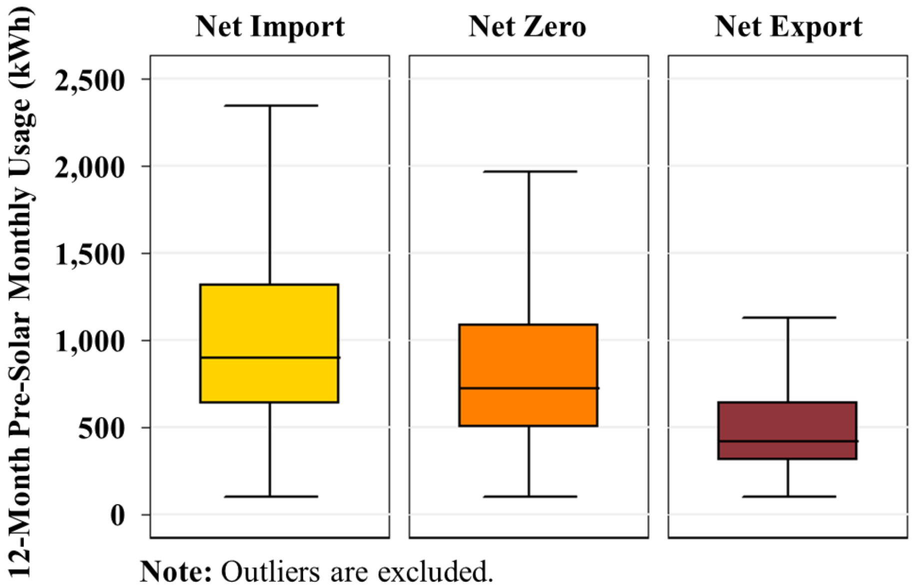
Note: The percentage energy consumption offset is calculated by dividing the estimated energy generated by rooftop PV by the 12-month pre-solar consumption, then multiplied by 100. The estimated PV energy output is calculated based on the size of the first PV system installed. The box graphs exclude outliers.
Source: HECO

Figure G.4: PV Installation Trend – *By PV Sizing Group*.



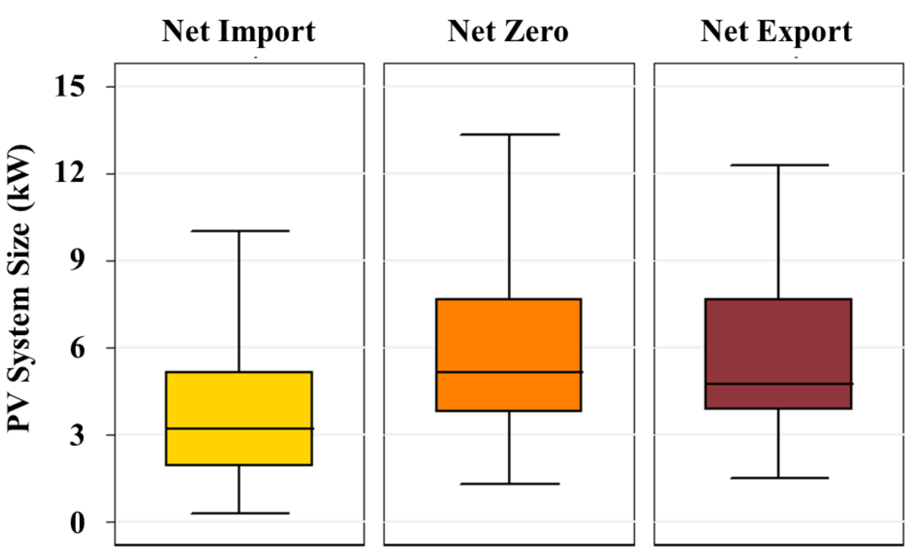
Note: Year of installation is based on the time a household's first PV system was installed.
Source: HECO

Figure G.5: 12-Month Pre-Solar Monthly Usage.



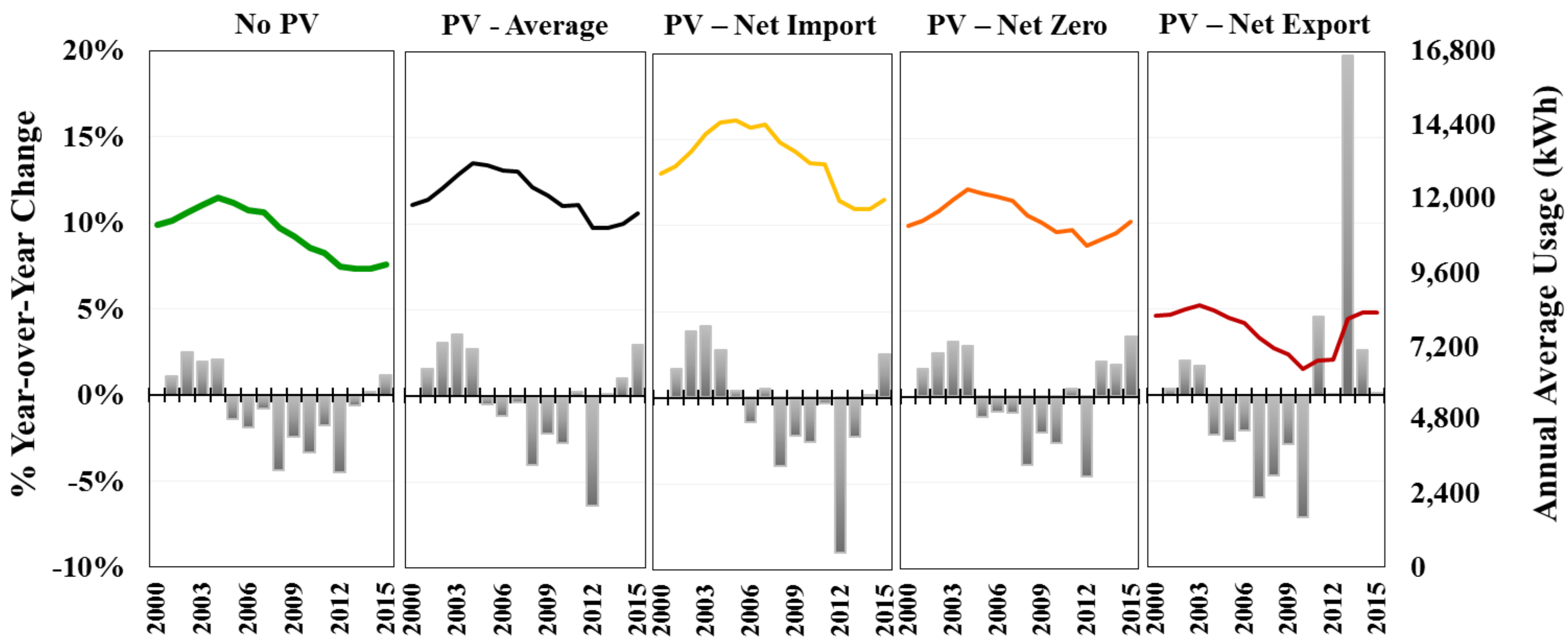
Note: Outliers are excluded.
Source: HECO

Figure G.6: PV System Size Distribution.



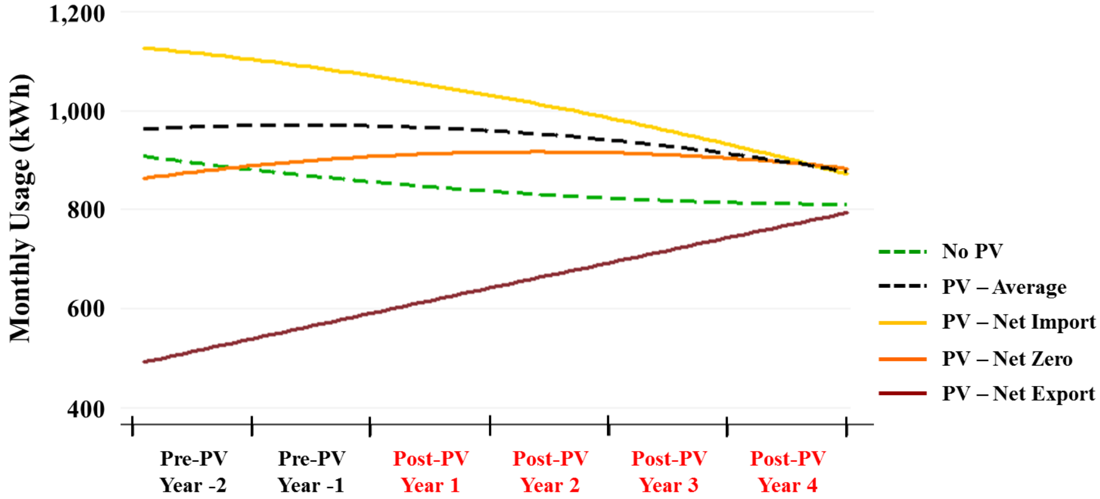
Note: We use nameplate capacity to determine the size of PV systems. Outliers are excluded.
Source: HECO

Figure G.7: Annual Average Usage & Percent Year-over-Year Change.



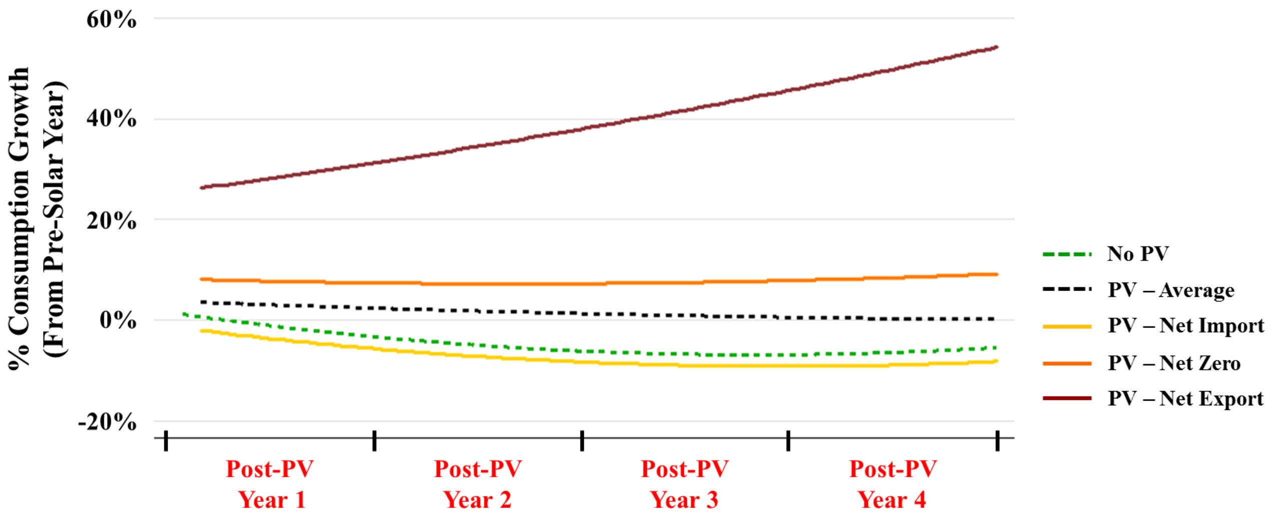
Note: The values of annual average consumption are calculated using gross monthly electricity usage. 2016 data is excluded since the study period only covers five months of 2016. The colored solid lines represent annual average monthly electricity consumption of households in each customer group. The grey bars show the percentage year-over-year change.
Source: HECO

Figure G.8: Consumption Trend – *2 Years Before & 4 Years after Installation*.



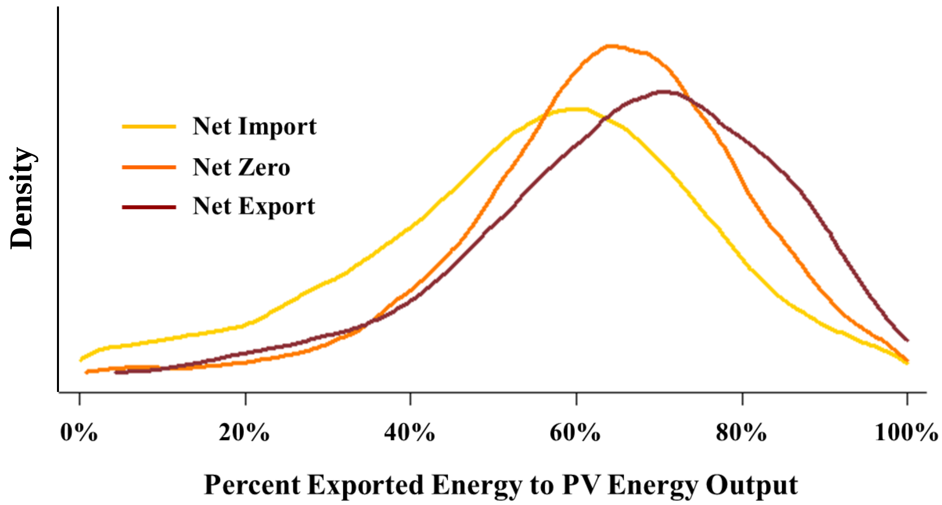
Note: For PV household, the first data point starts on the 24th month prior to solar installation, while for non-PV households it starts on January 2010. The black dash-line represents electricity consumption trend of all PV households.
Source: HECO

Figure G.9: The Rate of Change in Electricity Consumption after PV Installation.



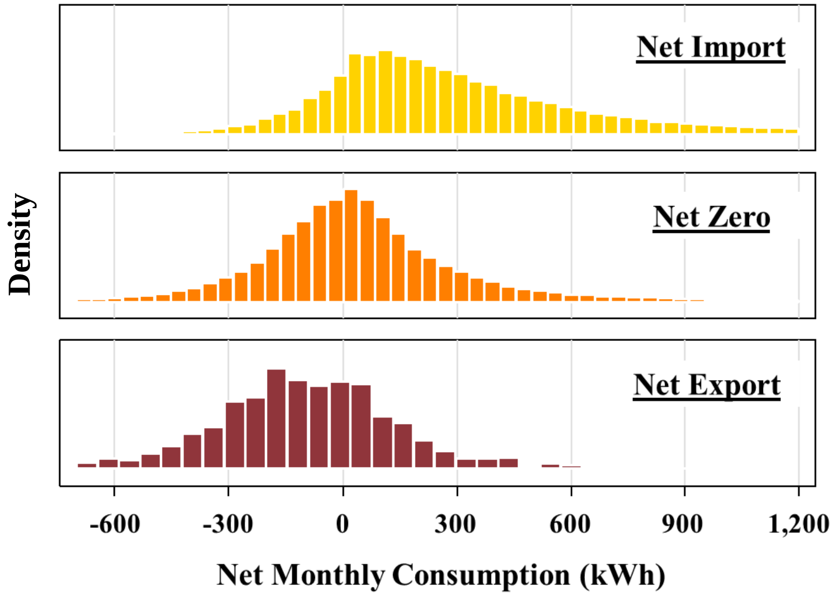
Note: The percent consumption growth rate is the post-solar consumption growth rate from 1-year pre-solar consumption. For non-PV households, January 2012 is the first data point (year 1). The black dash-line represents electricity consumption growth of all PV households.
Source: HECO

Figure G.10: Percent Exported Energy Relative to PV Energy Production (Kernel Density Distribution).



Note: The proportion of exported energy relative to overall estimated PV energy production is calculated by diving the amount of excess energy exported to the grid by the total monthly estimated PV electricity output.
Source: HECO

Figure G.11: Net Monthly Electricity Consumption.

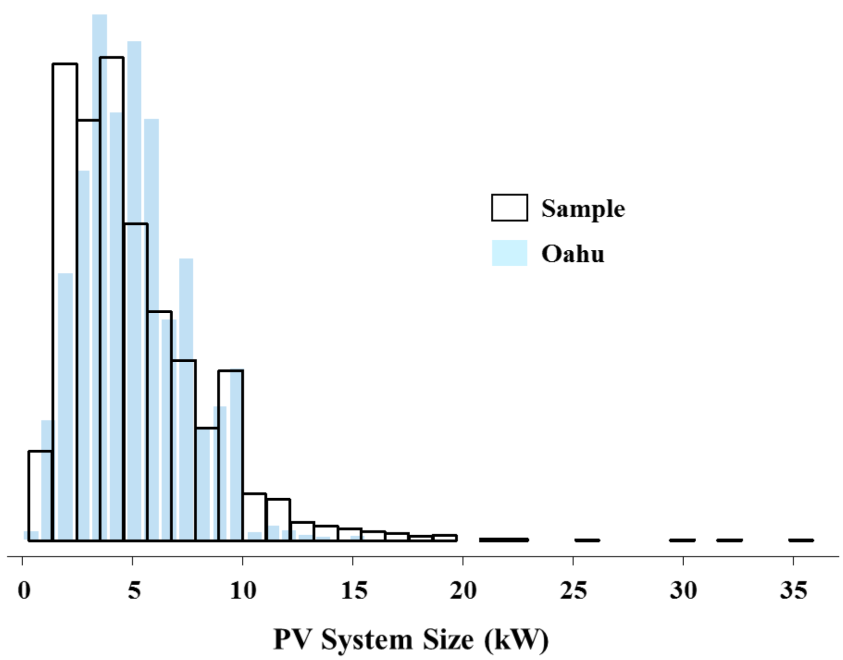


Note: Net monthly consumption is the difference in electricity bought and sold by a PV household.
Source: HECO

Appendix H

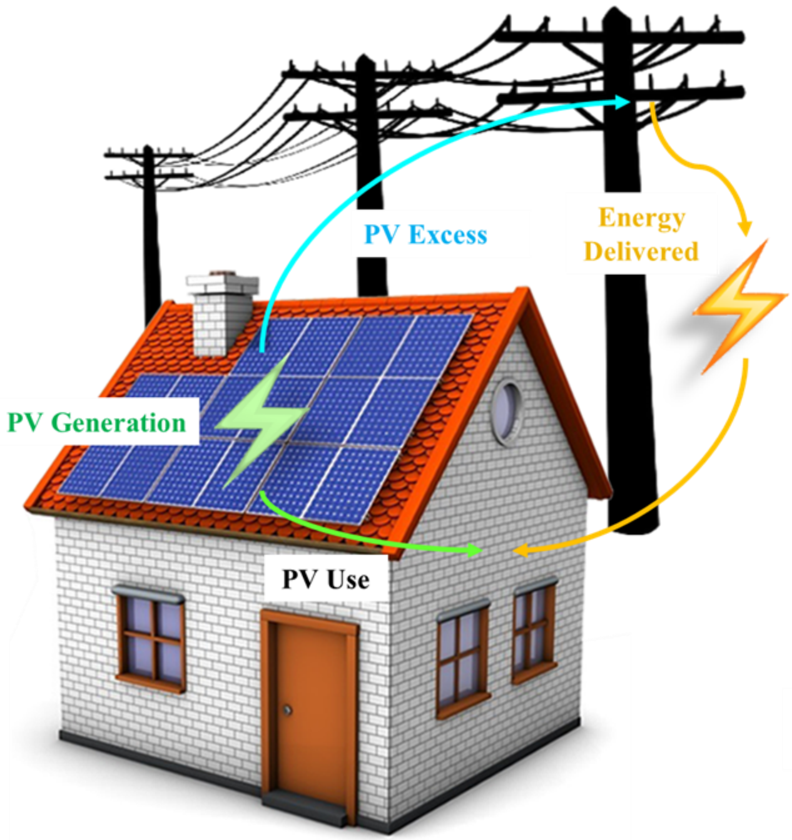
Additional Information

Figure H.1: PV System Size Distribution – *Sample VS Population (Oahu)*.



Note: The histogram depicts distributions in PV system size of the study sample and the population (Oahu).
Source: HECO

Figure H.2: Gross Electricity Consumption Calculation.



$$PV.Generation_{it} = PV.Use_{it} + PV.Excess_{it}$$

$$Gross.Usage_{it} = Energy.Delivered_{it} + PV.Use_{it}$$

$$Net.Bill_{it} = Energy.Delivered_{it} - Energy.Received_{it}$$

$$PV.Excess_{it} = Energy.Received_{it}$$

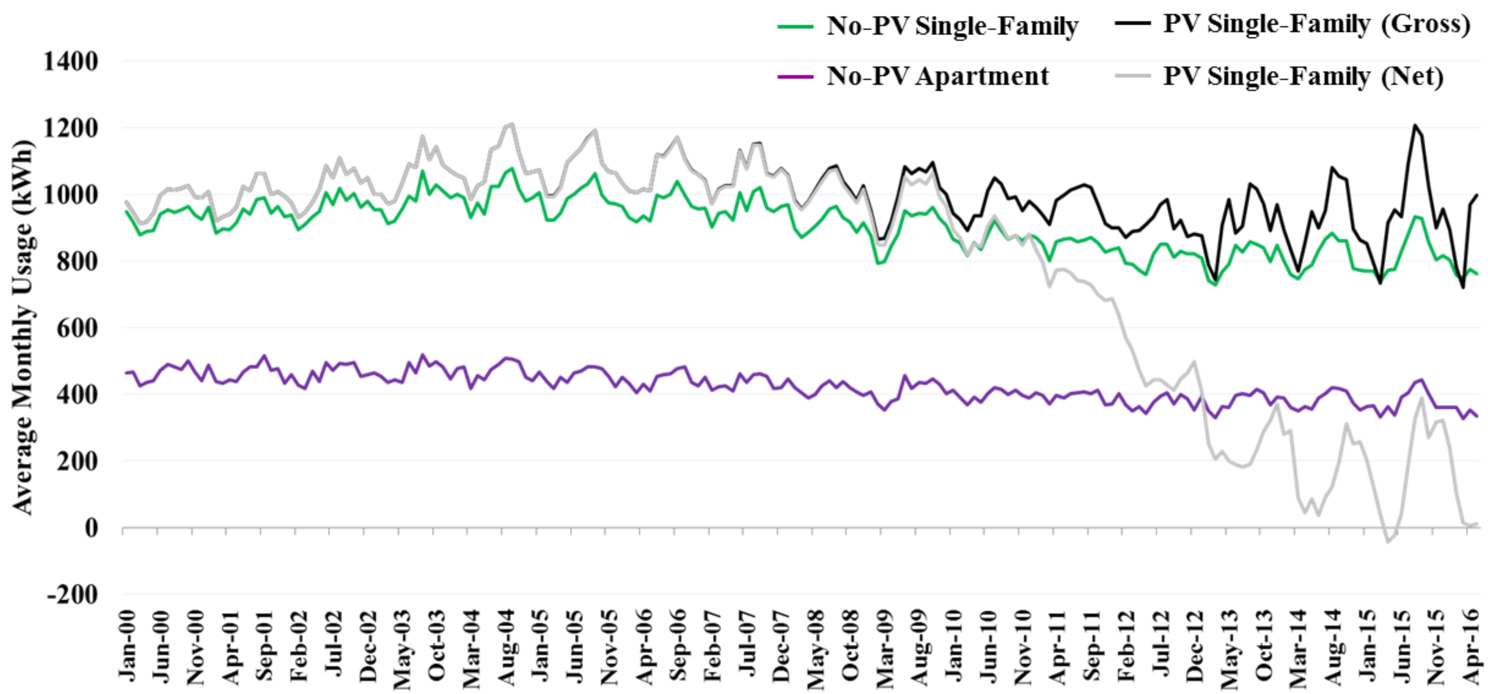
$$Gross.Usage_{it} = Net.Bill_{it} + PV.Generation_{it}$$

$$Gross.Usage_{it} = Energy.Delivered_{it} - Energy.Received_{it} + PV.Generation_{it}$$

$$Gross.Usage_{it} = Energy.Delivered_{it} - PV.Excess_{it} + (PV.Use_{it} + PV.Excess_{it})$$

Note: For a household i at month t, *PV.Generation* is the total amount of energy produced by a rooftop PV. *PV.Use* is the amount of energy produced by a rooftop PV and consumed on site. *PV.Excess* is the excess energy produced by a rooftop PV, not consumed on site, and exported back to electric grid. *Gross.Usage* is the total electricity consumption which is the sum of *Energy.Delivered* and *PV.Use*. *Energy.Delivered* is the amount of energy delivered/provided to a household by the utility and consumed on site. *Net.Bill* is the difference between *Energy.Delivered* and *Energy.Received*, where *Energy.Received* is the amount of energy the utility receives from a household's rooftop PV system (which is equal to *PV.Excess*).

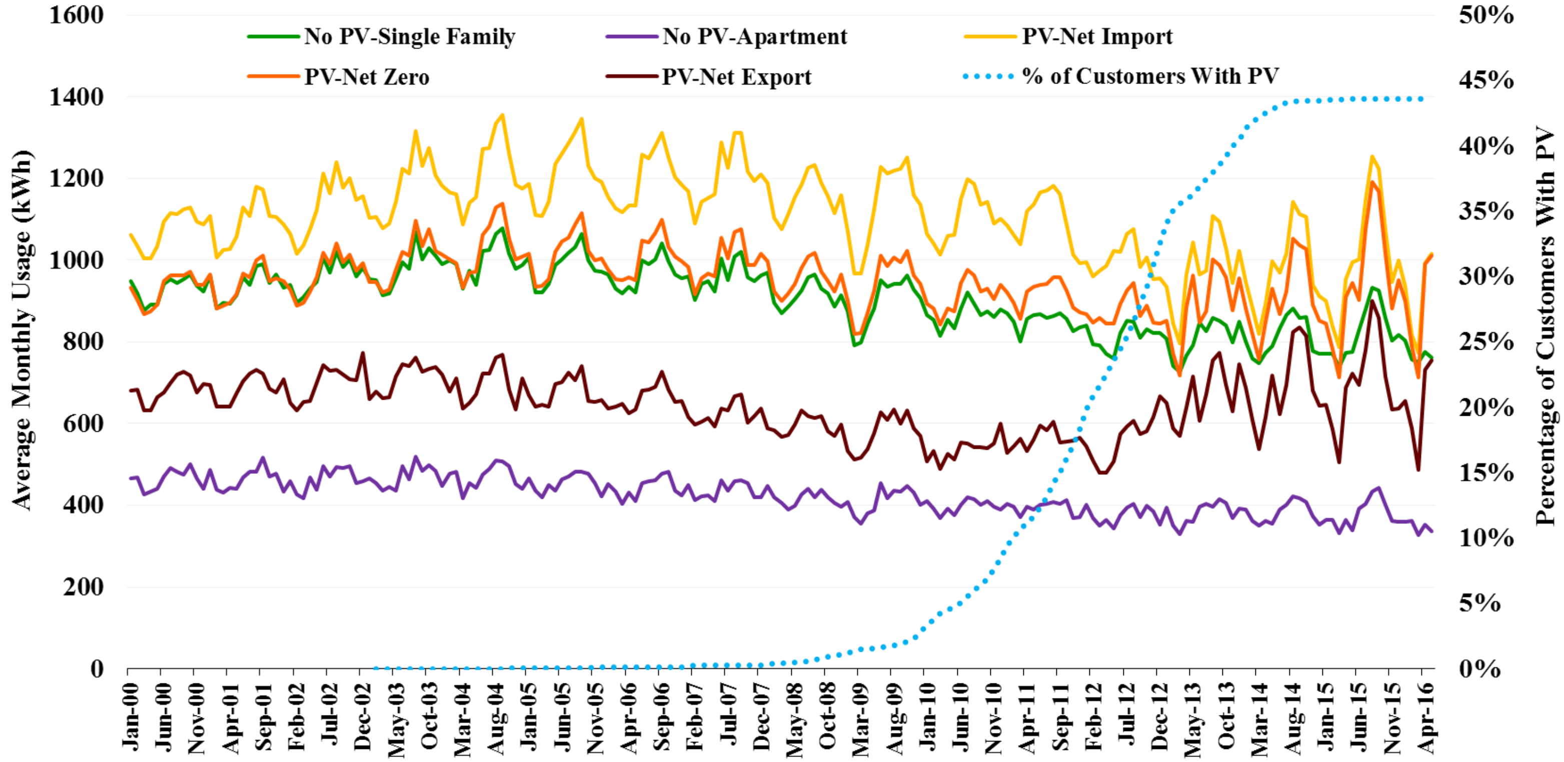
Figure H.3: Average Monthly Electricity Consumption – *No-PV & PV*.



Note: This figure shows average monthly electricity consumption trends of households in the study sample. The green and purple lines represent average monthly usage of residential households with PV, residing in single-family homes and apartment building, respectively. The black and gray lines depict gross (total) and net monthly energy consumption of single-family PV households, respectively. PV customers with at least one additional PV system installed after the initial PV installation were excluded.

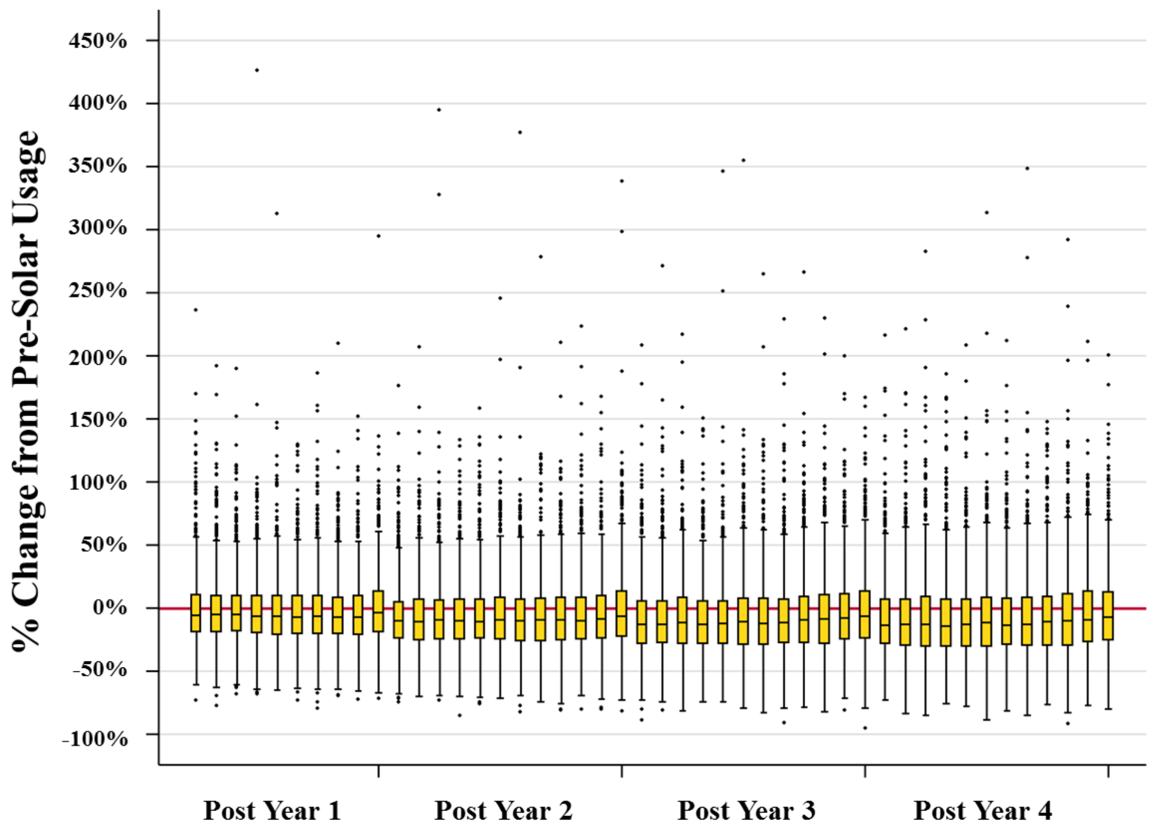
Source: HECO

Figure H.4: Average Monthly Electricity Consumption – No-PV & PV Sizing Group.



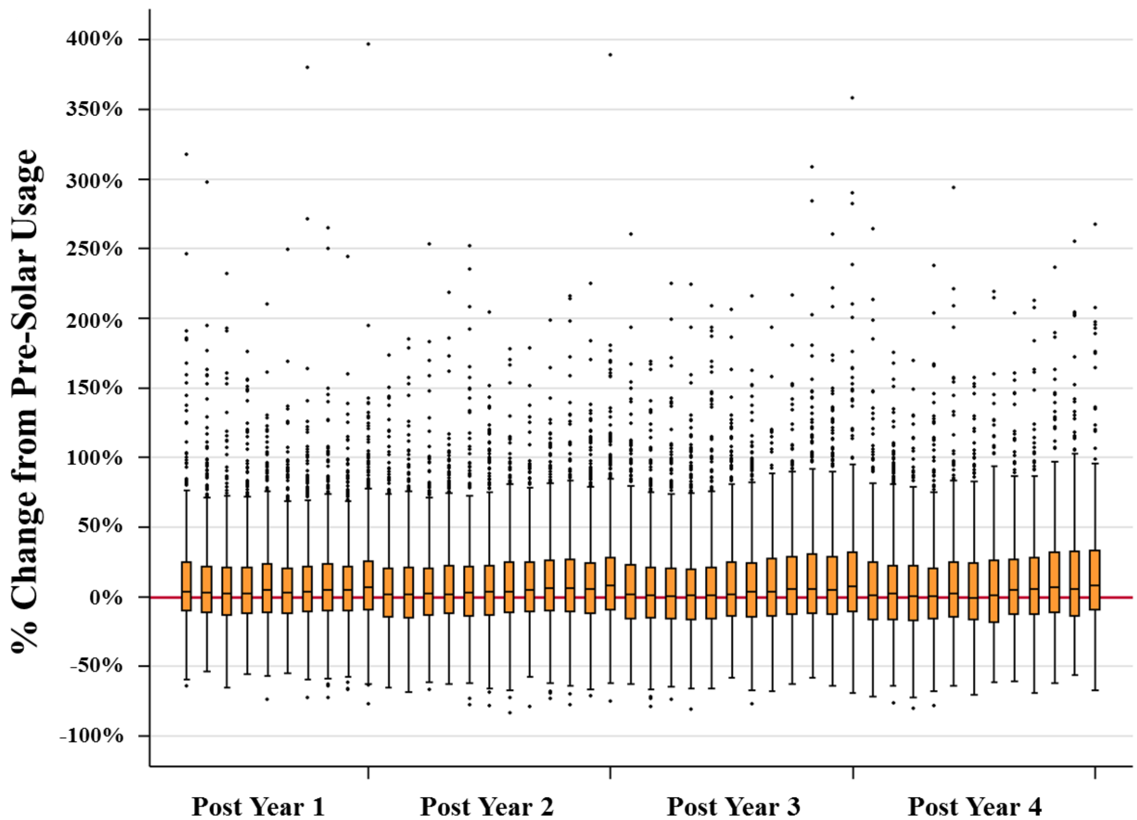
Note: The blue dash line depicts the percentage of PV customers to the total residential single-family customers in the study sample. The number of customers having PV installed is therefore different in each time period.

Figure H.5: Percentage Change from Pre-Solar Usage – *Net Import*.



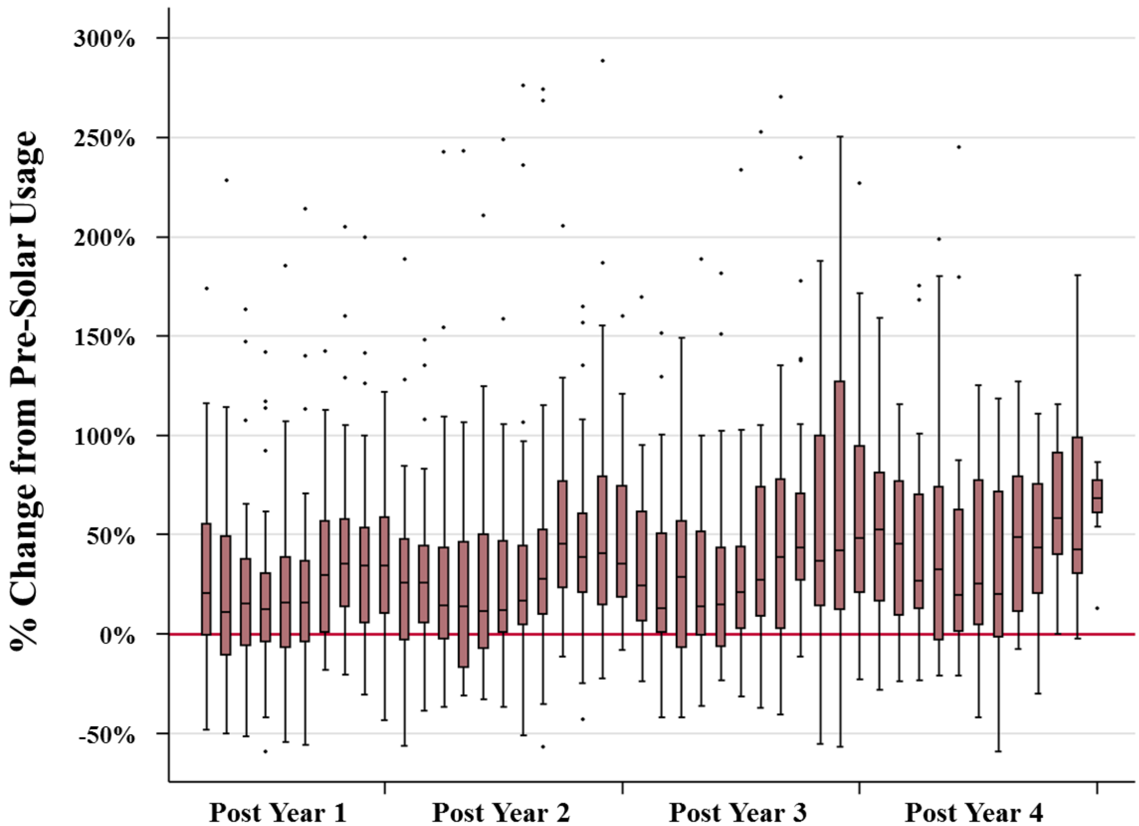
Note: Percentage change from pre-solar usage = $(post_t - pre_t)/pre_t * 100$

Figure H.6: Percentage Change from Pre-Solar Usage – *Net Zero*.



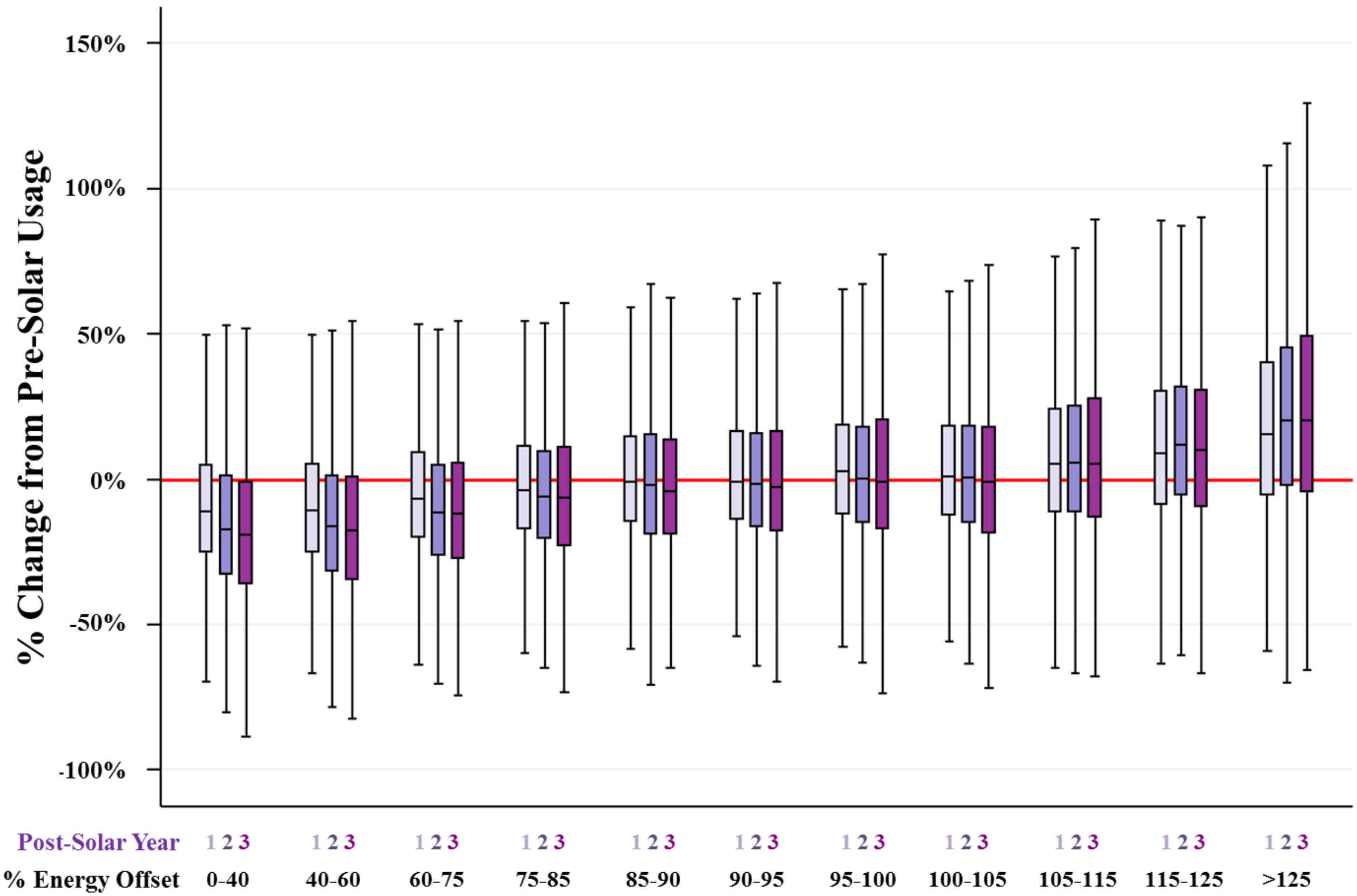
Note: Percentage change from pre-solar usage = $(post_t - pre_t)/pre_t * 100$

Figure H.7: Percentage Change from Pre-Solar Usage – *Net Export*.



Note: Percentage change from pre-solar usage = $(post_t-pre_t)/pre_t * 100$

Figure H.8: Percentage Change from Pre-Solar Usage – *Separated by Percent Energy Offset*



Note: For three post-solar years, this figure shows percentage consumption change after PV installation (compared to pre-solar usage) separated by average percentage of energy offset by rooftop PV.

Table H.9: PV Sizing Categories – *Sensitivity Analysis*.

Average (1 year Pre-Solar)

	Count	%
Net Import	859	41.0%
Net Zero	1,190	56.9%
Net Export	44	2.1%

Average (2 year Pre-Solar)

	Count	%
Net Import	920	44.0%
Net Zero	1,130	54.0%
Net Export	43	2.1%

Maximum (1 year Pre-Solar)

	Count	%
Net Import	1,570	75.0%
Net Zero	509	24.3%
Net Export	14	0.7%

Maximum (2 year Pre-Solar)

	Count	%
Net Import	1,761	84.1%
Net Zero	325	15.5%
Net Export	7	0.3%

Minimum (1 year Pre-Solar)

	Count	%
Net Import	423	20.2%
Net Zero	1,319	63.0%
Net Export	351	16.8%

Minimum (2 year Pre-Solar)

	Count	%
Net Import	374	17.9%
Net Zero	1,240	59.2%
Net Export	479	22.9%

Note: The tables above show how the number of customers in each PV sizing group changes with different indices and different pre-solar period. On the left hand side, the tables show the number of PV customers under each sizing category based on 1-year pre-solar monthly consumption. Taking into account any unobserved variations in energy consumption, the right-hand-side tables show slightly different results when 2-year pre-solar usage is used.

Table H.10: Number of Households with Additional Solar PV Installations.

	Number of Additional PV Systems				
	1	**2**	**3**	**4**	**5**
Net Import	863	281	62	9	1
Net Zero	1,187	44	0	0	0
Net Export	44	0	0	0	0
Total	2,094	325	62	9	1

Table H.11: Transitions across Sizing Groups – *PV Households with Additional Systems*.

Sizing Group	Count	%
Under-Under	95	3.81%
Under-Right	177	7.11%
Under-Over	9	0.36%
Right-Under	1	0.04%
Right-Right	31	1.24%
Right-Over	12	0.48%
Under-Under-Under	9	0.36%
Under-Under-Right	41	1.65%
Under-Under-Over	2	0.08%
Under-Right-Right	8	0.32%
Under-Right-Over	2	0.08%
Under-Under-Under-Under	1	0.04%
Under-Under-Under-Right	3	0.12%
Under-Under-Right-Right	3	0.12%
Under-Right-Right-Right	1	0.04%
Under-Right-Right-Over	1	0.04%
Under-Under-Under-Right-Over	1	0.04%
No Add-Ons	2093	84.06%

Note: Under = Net Import, Right = Net Zero, and Over = Net Export

Sizing groups calculation is based on pre-installation consumption.

Table H.12: Number of Households with & without Solar Hot Water Heater (SWH)

	Number of Samples			
	No PV	**Net Import**	**Net Zero**	**Net Export**
With SWH	104	499	376	35
No SWH	1,453	716	855	9

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